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Computational techniques for assessing the reliability and sustainability of electrical power systems: A review

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ABSTRACT

Power systems employ measures of reliability indices to indicate the effectiveness a power system to perform its basic function of supplying electrical energy to its consumers. The amount of energy required in a generating system to ensure an adequate supply of electricity is determined using analytical and simulation techniques. This study focuses on reviewing the generation reliability assessment methods of power systems using Monte Carlo simulation (MCS) and variance reduction techniques (VRTs). MCS is a very flexible method for reliability assessment of the power systems, by the sequential process it can imitate the random nature of the system components and can be broadly classified into two, sequential and non-sequential simulations. A brief introduction to MCS is provided. Unlike analytical methods, MCS can be used to quantitatively estimate the system reliability in even the most complex system generating capacity situations. The major drawback of the MCS is that it requires more computational time to reach for converging with estimated the values of reliability indices. This paper presents an effective methods for accelerating MCS in power system reliability assessment. VRT used is to manipulate the way each sample of an MCS is defined in order to both preserve the randomness of the method and decrease the variance of the estimation. In addition, the study presents detailed descriptions of generation reliability assessment methods, in order to provide computationally efficient and precise methodologies based on the pattern simulation technique. These methodologies offer significantly improved computational ability during evaluations of power generation reliability.

1. Introduction

The basic function of a power system is to supply electrical power efficiently to consumers as economically as possible, with a reasonable assurance of quality and continuity. The modern society required the to be continuously the supply of electrical energy on consumers demand [1]. A wide range of techniques are available for assessing engineering systems and evaluating their reliability indices, and these should be carefully interpreted and understood.

Generating capacity reliability indices assist in producing sufficient energy to satisfy demand using a given amount of energy consumption in the system. Generating capacity can be defined in terms of adequacy of as the installed generating capacity required satisfying a particular load demand. The amount of generating capacity required to ensure sufficiency of electricity supply is determined by evaluating the reliability indices of the power system. There are two main approaches; the use of analytical methods and the performance of simulations using the Monte Carlo simulation (MCS) [2,103,143].

Both approaches have advantages and disadvantages [4–7]. Analytical methods generally use basic knowledge and mathematical models, recounting and combining the probabilities and frequencies of system conditions to check reliability indices. MCS describes a problem as a sequence of actual experiments that determines the operating characteristics of a system and its components. Reliability indices are then evaluated by observing the experiments. In general, reliability evaluation depends on the analytical assessment methods [8] but introduces MCS as an alternative solution to illustrate the random behavior of a system and its components.

The advantage of MCS over analytical techniques is its improved capability to simulate the actual operation of a power system; hence, it provides a more accurate evaluation of reliability indices [1,9]. MCS is an extremely robust computer-based technique for estimating system reliability and, in most cases, applying MCS requires considerable computational time to obtain accurate and reliable results. Moreover, it

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requires input information in the form of distributions as well as the more conventional prospect values used in many analytical methods [10].

This work reviews reliability assessment methods for power systems generating capacity based on the use of MCS, supplemented by the application of applied VRTs since the number of samples required by MCS methods can be reduced using VRTs [101,142,144]. VRTs rely on presumed information concerning the analytical model of a system under simulation and are effective for reducing variance. The combination of VRTs and the Monte Carlo algorithm minimizes computational effort, and in many cases, the VRTs employed to provide the same general applicability as the standard MCS (sampling) method, but offer superior computational efficiency.

The main objective of this paper is to present efficient estimation and accurate models based on a pattern simulation technique to minimize computational efforts significantly while evaluating generation system reliability. Reliability evaluation is an important aspect of any generation system, many techniques have been developed to assess power system reliability. Hence, in this study, focus on a comprehensive review of the probabilistic techniques applied to reliability evaluation of the generation systems. The two main probabilistic techniques that the analytical approach and the MCS approach. Father, this study displays by using the various methods are available in the literature, that used to improve the MCS approach namely variance reduction techniques. In addition, the study presents descriptions of the new robust computational intelligence techniques that are widely used in power system generation applications. These techniques are often utilized to solve the complex problems in power system, which are difficult to solve with conventional methods.

The remainder of this paper is arranged as follows: Section (2) contains an analysis of a power system demonstrating that the main functional zones provide the most convenient basis for its division. Section (3), explains the basic principles of the analytical methods and the Monte Carlo simulation. Section (4), illustrates the Variance Reduction Techniques and discusses the importance of sampling in Monte Carlo simulation. Section (5) clarifies several methodologies for reducing computational effort by combining the Monte Carlo simulation and the Variance Reduction Techniques. Finally, Section (6) presents the conclusions of the work.

2. Generation reliability assessment

Quantitative reliability assessments should not only evaluate a system's actual physical components in terms of performance and random behavior, but also the overall requirements, procedures, and engineering issues inherent in the system's operation [11]. A power system is an extremely complex, advanced and integrated structure [12]; even the most advanced computer programs lack the capacity for comprehensive, holistic interpretation for these systems. Consequently, power systems are frequently divided into appropriate subsystems that can be separately analysed.

The most convenient means for dividing a power system are its main functional zones; namely its generating capacity systems, composite systems, and distributed power systems. Hierarchical levels (HL) have been developed [13] to determine an identical means of grouping and identifying the aforementioned functional zones, as illustrated in Fig. 1. The figure shows that the primary level (HLI) refers to the generation facilities and their capability to satisfy pooled system demand; the second level (HLII) refers to the composite generating and transmission system and its capability to deliver energy to other major points; and the last level (HLIII) refers to the entire system as well as the distribution system and its capability to satisfy the energy demands of individual customers.

The main function of a power system is to supply consumers with electrical power as economically as possible at an acceptable level of quality [14,15]. The term reliability index, when applied to generation systems, refers to performance measures of the generating system capacity that can influence the continuity of electrical power supply to the customer. Two basic concepts are used in system capacity assessments: adequacy and security. Generating capacity requirements can also be separated into two basic categories: static capacity, which correlates with the long-term estimate of overall system demand; and operating capacity, which is a short-term correlation with the actual capacity required to meet a specified load.

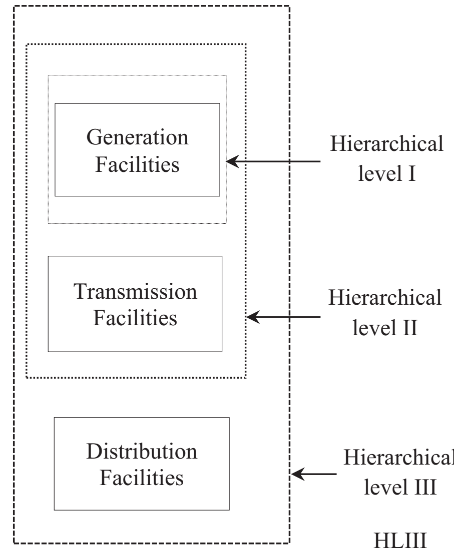

Fig. 1. Hierarchical reliability assessment levels [1].

Adequacy assessment considers the entirety of the facilities within a system and their sufficiency to satisfy consumer load demands. Adequacy is therefore associated with a static level of demand which is exclusive of transient system disturbances [2]. The evaluation of generating adequacy reliability can, therefore, be addressed by using either probabilistic or deterministic method. Over the last few decades, a large number of publications have proposed different probability techniques for generation reliability evaluation [16–23]. Adequacy correlates with the system's ability to satisfy load demand in the case of planned or unplanned capacity outages.

Inadequacy can result from insufficient available generation capacity or inability of the transmission or distribution networks to transfer energy to the customer load points. Often, therefore, calculation of the adequacy indices used in assessing generation power systems at one of the three hierarchical levels depends fundamentally on the expected values of a random variable which representing the average value of the reliability indices within a probability distribution. There are many indexes to assess the adequacy of a power system as can be seen in Fig. 2.

3. Adequacy assessment methods

Determining the amount of generating capacity required to satisfy load demand is an important concept in electrical power system operation and planning. The modern approach to evaluating reliability indices for generation system capacity is based on two alternative assessment methods for predicting the reserve capacity required to meet the load demand with a predetermined level of reliability. These assessment methods comprise analytical and simulation techniques and both approaches are used in electric power utilities at the present time.

Simulation techniques are used to imitate unpredictable performance in power systems, either in a random or sequential way [1,9]. Analytical assessment methods are easily and simply applied using mathematical analysis to derive precise analytical solutions to the value of reliability indices from the model. Monte Carlo simulation is the preferred method for reliability assessment of large and complex systems due to the realism it introduces, therefore, it is adopted as the benchmark when comparing accuracies among different computational methods. Both assessment methods have merit and demerit and can be very powerful when properly applied.

3.1. Analytical assessment methods for reliability adequacy

Analytical assessment methods use a mathematical model to represent system states and evaluate reliability indices from the model using mathematical solutions. In general, an analytical approach is very efficient to assess the reliability if not taking into consideration the complex operating conditions and the random failure probability for system components. Analytical methods therefore offer potential advantages over simulation methods in terms of reduced computing effort when assessing expected reliability indices. They can be divided into three categories: Enumeration Methods, Population Based Methods, and Approximate Methods.

Enumeration Methods, calculate the probabilistic array of a system state associated with its capacity level model. This model is combined with the load model to construct a risk model. The first enumeration method is the loss of load expectation method, which tests the probability of a simultaneous outage of generating units against a model of peak load. Loss of load expectation indicates a probability of system load exceeding the available generation capacity. A second enumeration method is the frequency and duration method, which addresses those factors as well as probability [24,25,44]. The frequency and duration method requires additional data (the transition rate parameters μ and λ in addition to unavailability and availability) to that required by the earlier method. Both techniques are widely used to evaluate the static capacity relevant to a specific generation system [2,5,6,26,43].

This paper also explained the population-based intelligent search (PIS) which employed an optimization search tool to calculate the reliability indices of power generating system. PIS can be considered as a viable replacement for the analytical and MCS techniques in assessing non-chronological system reliability indices.

PIS methods are basically enumeration algorithms, which account for differing states in the system's state space. These methods make use of optimization tools and evolutionary programming, such as genetic algorithms (GA), particle swarm optimization algorithms (PSO), intelligent state space pruning (ISSP), and evolutionary computation (EC); developed to facilitate calculation of reliability indices [34,46,63,119,145–155]. PIS methods also attempt to discover the majority, if not all, of the available states, in order to calculate a good approximation of the reliability indices [27]. A significant number of research papers in the power system reliability assessment in literature have introduced techniques using PIS methods, which were used to reduce the search space and the computational efforts.

Approximate methods are now used for examining a generation system's suitability for modeling. While traditional algorithms for generation system modeling are based on recursive algorithm procedures, these algorithms are theoretically accurate for calculating discrete probability distributions for generation capacity outages. Approximate methods use the continuous probability distribution function for formulating an approximate generation system model [28].

Analytical assessment methods have two main drawbacks when evaluating power generation systems, firstly relating to the system's complexity and secondly to the number of potential system states, both of which increase exponentially with the number of system components.

3.2. Monte Carlo-based assessment methods

This approach, usually known as the Monte Carlo simulation, imitates the actual process and random behavior of the power system under consideration. The failure and repair of the system are simulated using random variables and probability distributions of the system states, which mimic random system operational behavior such as component failures, etc. The main objective of the simulation method is to generate the expected or average values for system reliability indices.

Simulation methods, therefore offer increasing advantages over analytical methods as systems become larger and more complicated; until a point is reached where analytical methods are no longer suitable for assessing system reliability. Analytical methods often require contingency enumeration of a large number of states before they can be reduced to a representative model. Monte Carlo simulation methods avoid this problem by sampling a characteristic set of system states.

Monte Carlo methods generate solutions as a parameter proportionate to a population and, using a random sequence of numbers to construct a sample of the population, obtain a statistical estimate of the parameter [29]. Monte Carlo methods can be broadly classified into two main types according to the way in which system states are sampled; non-sequential Monte Carlo (random sampling), and sequential Monte Carlo (chronological sampling) simulations [1,5,9,30–35,38]. Sequential MCS typically require higher computational effort than non-sequential MCS [36]. Pseudo-sequential [37–39], quasi-sequential [40–42] and pseudo-chronological MCS [38] do not adopt either a chronological or a pure state-space representation [1,9,43]. These approaches are reviewed in the following sections:

3.2.1. Non-sequential method

In the non-sequential, or random, simulation approach towards estimating generating capacity, each consecutive sample of system states is randomly selected completely independently from previous and subsequent samples. Therefore, in a non-sequential Monte Carlo assessment, system components are sampled without considering any time dependency between coherent states. In the case of the two-state Markov model (operation and failure) for conventional generators, the reliability indices estimation based on non-sequential MCS (state-sampling) is represented by the following mathematical equation:

$$\bar{E}\,[F] = \frac{1}{NS}\sum_{i=1}^{NS} F\,(X^i) \tag{1}$$

where X^i is a sampled system state; $F(X^i)$ is the outcome of the test function F; NS is the number of samples, and $\bar{E}[F]$ is the expectation of a given reliability indices represented by F [44].

For example, the probability of a system load curtailment (LOLP), which is a traditional reliability index [45], is evaluated using the test function F and defined as:

$$F_{LOLP}\,(X^i) = \begin{Bmatrix} 0 & if & x^i \in S_{xf} \\ 1 & if & x^i \in S_{xs} \end{Bmatrix}, \tag{2}$$

where S_{xs} denotes the success states; S_{xf} denotes the failure states and $S_x = S_{xs} \cup S_{xf}$, which represents all the system states. All the basic reliability indices can be obtained using Eq. (1), depending on the definition of the test function [46] Eq. (2).

3.2.2. Sequential method

The sequential Monte Carlo assessment method can be used to perform the system analysis in a chronological manner. In applying sequential MCS for estimating generating capacity, each subsequent system state sample is related to the previous set of system states. The sequential approach moves consecutively through time, and system states are simulated indirectly. In the case of the generating capacity assessment addressing the two-states Markov model system compo-

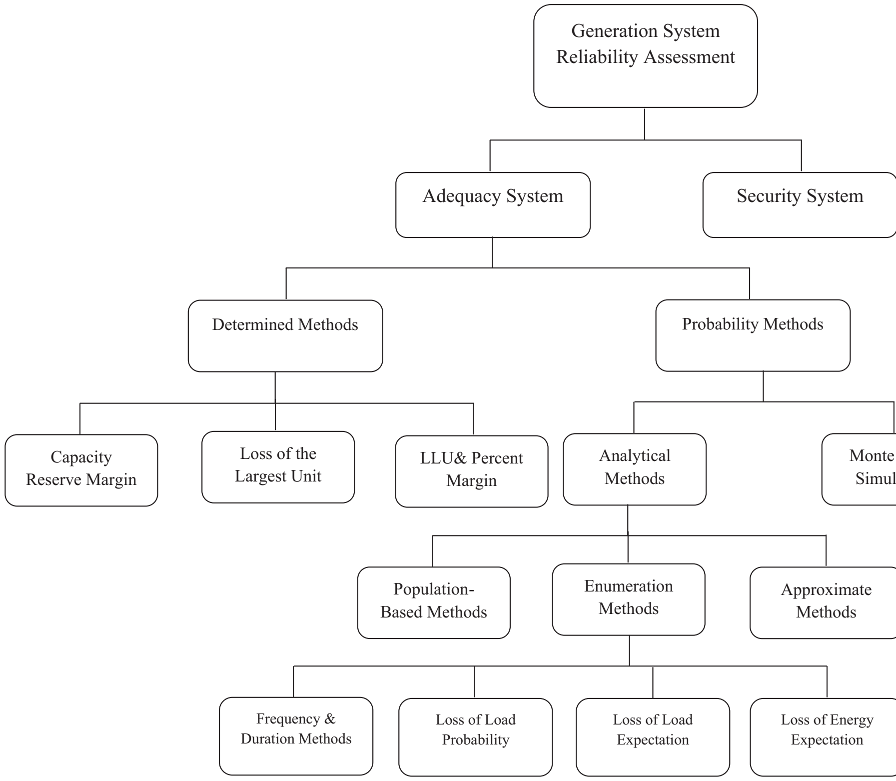

Fig. 2. Categorization of Generation System Reliability Evaluation Indices.

nents (upstate and down state), reliability indices estimation based on sequential MCS is represented by the following mathematical equation:

$$\bar{E}\,[F] = \frac{1}{NY}\sum_{i=1}^{NY} F(\{X_n\}_{n=1}^{Si}), \tag{3}$$

where $\{X_n\}_{n=1}^{Si} = \{X_1 \ldots, X_{Si}\}$; $S_i \in N$ is the synthetic gradation of system states X in period i; and NY is the number of simulated time. The LOLP index is evaluated using the test function F and defined as:

$$F_{LOLP}(\{X_n\}_{n=1}^{Si}) = \frac{1}{T}\sum_{n=1}^{Si} d(X_n) \times F_{LOLP}(X_n) \tag{4}$$

where X_n is the n^{th} state of the sequence; T is the duration of the synthetic;, simulated time is (8760) hour; $d(X_n)$ is the duration of state X_n; and $F_{LOLP}(x_n)$, is the outcome of Eq. (2).

3.2.3. Convergence criterion

The MCS approach is a fluctuating convergence process, therefore the simulation should be terminated when the estimated reliability index values achieve a specified degree of confidence. The purpose of using a terminated simulation process is to provide a compromise between required accuracy and computational cost. The coefficient of variation is often used as the convergence criterion in MCS and the coefficient of variation for any reliability index is defined as:

$$\alpha = \frac{\sigma}{E(X)} \tag{5}$$

where the estimate of the reliability indices is $E(X)$, and the standard deviation is σ. In other words, the coefficient of variation can be using to expressed accuracy level of the MCS, in order to guarantee reasonable accuracy in a multi-reliability index study [1].

Convergence criteria for MCS algorithms are based on the differences recorded between the reliability index values under observation. The variance criterion, therefore indicates the extent to which a random variable deviates from its expected value. A small variation in this parameter is desirable since it results in improved MCS accuracy. Such an improvement may be achieved by either increasing the number of samples, thereby leading to a consequent increase in computational effort, or by employing VRTs, which may produce better estimates without changing the number of samples.

4. Sampling reduction techniques

The number of samples required by the sequential MCS and non-sequential MCS techniques can be reduced using VRTs. These techniques rely on model information collected a priori for the system under simulation and are effective for reducing variance. Computing time and variance are directly affected by system analysis requirements and the selected sampling techniques. The standard deviation is given by the following equation:

$$\sigma = \frac{\sqrt{V(z)}}{\sqrt{N}} \tag{6}$$

where the sample number is N, and the unbiased sample variance is $V(z)$. The equation shows that decreasing the unbiased sample variance can decrease the standard deviation of MCS, and similar effect when increasing sample number has on the accuracy of MCS.

The MCS method can easily incorporate all chronological aspects of power systems into the simulation, such as load demand fluctuation, failures on transmission lines, time dependent sources, etc. In addition, it is the only method capable of providing the probability distribution of the reliability indices. Despite these advantages, this method is time inefficient due to the sequential process for sampling system states [1,9,37]; and one way to make the MCS method more time efficient is to use VRTs. In sampling terms, these techniques aim to decrease the variance in estimates of the reliability indices without affecting their expected value [1,9,47–53,68,69,116]. VRTs can reduce the amount of sampling needed to obtain indices estimates to the desired level of accuracy, or increase the accuracy of the estimates for the required number of samples.

Among a number of VRTs that are very useful in assessment a power system reliability [1] are Antithetic Variables (AV) [47–49]; Dagger Sampling (DS); Control Variates (CV), Importance Sampling (IS) [51,52,138], and Stratified Sampling (SS) [47]. A further interesting way of reducing the variance of reliability indices is by using Latin Hypercube Sampling (LHS) techniques [54,116], and integration of these VRTs [95] has been used to speed up the process of estimating the reliability indices using MCS.

Recent work has shown that the sampling efficiency of MCS methods can be improved by using Importance Sampling (IS) [55]. This is a significant technique which is used to reduce sample numbers and includes the following methods: variance minimum method; cross-entropy method; weighted importance sampling; sequential importance sampling, and response surface estimation via importance sampling [42]. The following sections briefly present IS and other VRTs available in the literature:

4.1. Antithetic Variates (AV)

This technique is based on finding two unbiased estimators for the unknown parameter which have a strong negative correlation. If there are two unbiased estimators θ_1 and θ_2 , then:

$$\theta = \frac{1}{2}(\theta_1+\theta_2) \tag{7}$$

From the above equation, the estimator value is still an unbiased. The variance of θ is:

$$V(\theta) = \frac{1}{4}V(\theta_1)+\frac{1}{4}V(\theta_2)+\frac{1}{2}cov(\theta_1, \theta_2) \tag{8}$$

Clearly from Eq. (7), if *cov* (θ_1, θ_2), is strongly negative, the overall variance can be reduced [1,56].

4.2. Dagger Sampling (DS)

This method is suited to random variables with only two possible outcomes and small probability events. In power system reliability evaluation, the system components can be simulated by a two-state (up and down) and small failure events probability. This technique is discussed from the reliability evaluation point of view in more detail in Refs. [1,56].

4.3. Control Variates (CV)

This method [1,56,57] is based on an understanding of difference sampling between the result from the subject problem and a simplified model to which a solution is known. If A and B are two random variables with robust correlation, a new random variable D can be defined as:

$$D = B-A+E(A) \tag{9}$$

The mean value of E(A) can be obtained from analytical methods, proving that D and B have the same expected value:

$$E(D) = E(B)-E(A)+E(A) = E(B) \tag{10}$$

The variance of D is expressed by:

$$V(D) = V(B)+V(A)-2COV(B, A) \tag{11}$$

The covariance between B and A is *cov* (B, A). Since B and D have powerfully correlated, the variance of D is smaller than the variance of B. Variable A is called the control variable (CV). Some power system applications of this can be used to evaluate system indices for composite generation and transmission systems [56].

4.4. Importance Sampling (IS)

Is a method for changing the Probability Distribution Function (Pdf) of sampling in such way that the events which make the greatest contributions to the simulation results have greater occurrence probabilities. An integral can represent an expected value of a parameter and therefore the problem of estimating an integral by the MC method is equivalent to the problem of estimating an adequate index in reliability evaluation. The importance sampling technique can be illustrated using the problem of estimating an integral. If an indefinite integral function $g(x)$ is non-negative within interval [0,1], then $g(x)$ can be expressed as:

$$I = \int_0^1 g(x)dx. \tag{12}$$

Using the estimated method, the integral can be expressed as:

$$I = E(g(U))\approx\frac{1}{N}\sum_{i=1}^{N} g(x_i) \tag{13}$$

where U is random number uniformly distributed between [0,1]. Where, $U1$, $U2$ and $U3$ are three random numbers obtained from the uniform distribution, sampling between [0,1]. These random values make different contributions to the integral; $U2$ and $U3$ have less influence than U1 which designates that uniform sampling is unreasonable.

If the Probability Distribution Function (Pdf) for sampling is represented by the function $f(x)$ which has the same shape as $g(x)$, then the random numbers which can make a greater contribution to the integral value have larger occurrence probabilities. Dividing and multiplying $g(x)$ by $f(x)$, the integral can be expressed as:

$$I = \int_0^1 \frac{g(x)}{f(x)}f(x)d(x) \tag{14}$$

The function $f(x)$ representing the new PDF is called the importance sampling density function. If $\theta = g(x)/f(x)$ then according to the estimated method the integral equals the expected value θ:

$$I = E[g(x)/f(x)] \tag{15}$$

The variance of θ is:

$$V(\theta) = \int_0^1 \frac{g(x)^2}{f(x)^2}f(x)dx-I^2 \tag{16}$$

If $(x) = g(x)/I$, the variance of θ would be zero:

$$V(\theta) = I\int_0^1 g(x)dx-I^2 = 0 \tag{17}$$

It is impossible to make $(x) = g(x)/I$, because I, is unknown.

The variance can be reduced if $f(x)$ is shaped similarly to the shape of $g(x)$. In power systems reliability evaluation, the IS technique [1,57] can be used to address difficult problems in practical applications like sample hydrological or load states.

4.5. Cross-Entropy (CE)

The traditional MCS method for estimating rare-event probabilities requires a large simulation effort, therefore the Cross-Entropy technique was first introduced by Rubinstein [58,59]to augment earlier work on variance reduction [60], enabling the computation of rare events for which the probabilities of occurrence are very small. The CE approach is a well-known Monte Carlo technique for rare event estimation and optimization [61]. The technique is based on the repeated sampling process, wherein each iteration includes two steps: (a) generating random data according to a specified technique and (b) updating the parameters of the random technique based on that data to produce a better sample in the next iteration [62].

The CE method is demonstrated by assuming that $g(X)$ is a probability distribution belonging to the family of densities $f(X; v)$, where v is a vector of reference parameters. Likewise, $f(X)$ can be rewritten as $f(X; u)$, where u is also a vector of reference parameters

[63]. The core of the CE method is the minimisation of the *Kullback-Leibler* distance between *g(X)* and $g^*(X)$ [64], which represents the optimal IS distribution to achieve a substantial reduction in variance. This distance is defined as:

$$D(g^*(X), g(X)) = E_{g^*}\left[\mathrm{Ln}\frac{g^*(X)}{g(X)}\right] = \int g^*(X)\mathrm{Ln}g^*(X)dX - \int g^*(X)\mathrm{Ln}g(X)dX \quad (18)$$

The equation can minimize to:

$$max \int g^*(X)\mathrm{Ln}g(X)dX \quad (19)$$

by replacing.
$g^*(X), g(X), and\, f(X)$, by $f(X;v), f(X;u)$ in Eq. (19) as shown:

$$max \int \frac{H(X)f(X;u)}{\theta}\mathrm{Ln}f(X;v)dX \leftrightarrow max_v E_v[H(X)]\mathrm{Ln}f(X;v) \quad (20)$$

Naturally, the optimal vector of parameters v^* is the outcome of this optimization problem. Assuming that IS can be used iteratively to use to solve Eq. (20), then in the first iteration of this procedure, IS will use a new sampling function *f(X; v)*. Accordingly Eq. (20) is rewritten as:

$$max_v E_w[H(X)]\frac{f(X;u)}{f(X;w)}\mathrm{Ln}f(X;v) \quad (21)$$

The respective optimal vector of reference parameters v^* is:

$$V^* = argmax_v E_w[H(X)]W(X;w,u)\mathrm{Ln}f(X;v) \quad (22)$$

where $W(X;w,u) = f(X;u)/f(X;w)$. One way to solve Eq. (22) is to follow a stochastic program:

$$\tilde{v}^* = argmax_v \frac{1}{N}\sum_{i=1}^{N} H(X_i)W(X_i;w,u)\mathrm{Ln}f(X_i;v) \quad (23)$$

where N is the number of samples drawn from *f(X; w)*.

Taking advantage of the fact that Eq. (23) is often convex and differentiable with respect to *v,* an analytical solution to v^* rather than an estimate can be obtained [42]. Moreover, if f(X; v) belongs to the *Natural Exponential Family* [65], the entry *j, j=1,...., d*, of the vector can be calculated via:

$$v_j = \frac{\sum_{i=1}^{N} H(X_i)W(X_i;w,u)x_{ij}}{\sum_{i=1}^{N} H(X_i)W(X_i;w,u)} \quad (24)$$

This last Eq. (24), [42] shows that it is possible to create an IS based multi-level algorithm to improve iteratively the reference parameters v_j*, j=1,..., d*, until the optimal vector v^* for the target defined *E[H(X)]* is obtained.

4.6. Stratified sampling (SS)

Stratified sampling can be considered the similar to the concept of importance sampling. The idea is to divide the system into different subpopulations referred to as strata and to draw more samples into subintervals that give greater contributions to the final results. For more details see references [1,2,55,56].

4.7. Latin Hypercube Sampling (LHS)

LHS was first introduced by McKay [50]. It is a combination of stratified and random sampling methods that can be used to reduce the compute time of the MCS.

LHS is an effective VRT method that avoids the difficulties of SS for high-dimensional sample spaces. If SS is used for a space composed of D-dimensional uniform random variables, whose N/m is the number of samples per stratum, $(N/m)^D$ samples would have to be drawn in the expectation of at least one sample being drawn from every stratum. To address this problem, LHS proposes the stratification of the probability distribution of the random variables rather than the entire sample space.

The practicability of drawing a sample according to LHS method is notable. Consider a vector of D-dimensional independent uniform random variables $X = (X^1,\ldots,X^D)$, and a scalar function *H(X)*. Fixing *m* as the number of strata per random variable, which must be equal for all variables; and *N* as the total number of samples, generates *n=N/m* independent samples $\{U_i^1,\ldots,U_i^D\}$, $U_i = (u_{i1},,u_{im})$, $u_i \sim U(0,1), i = 1,\ldots,n$.

Additionally, generating (*n*) independent permutations, $\{\pi_i^1,\ldots,\pi_i^D\}$, $\pi_i = (1,\ldots,m), i = 1,\ldots,n$, then accordingly, (*m)* samples of *X* are generated in each iteration *i,* by the LHS technique [66]. Hence, the sample $X_{ij}, j = 1,\ldots,m$, is:

$$X_{ij} = \frac{\pi_{ij}^1 + 1 - u_{ij}^1}{m}, \ldots, \frac{\pi_{ij}^D + 1 - u_{ij}^D}{m} \quad (25)$$

Finally, the LHS estimator test function can be described as:

$$E[H(X)] = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{1}{m}\sum_{j=1}^{m} H(X_{ij})\right] \quad (26)$$

5. Methodology for reliability assessment

Systems adequacy evaluation using MCS is divided into two main parts; state sampling and state evaluation. The most earlier literature on this work has focused on developing techniques for state sampling. Methods based on probability concepts such as MCS can be useful in assessing high-performance electrical power systems.

The general steps in the sequential MCS algorithm used for the reliability assessment of generation and composite systems are based on the following:

- *Step 1:* Define the maximum number of years (*N)* to be simulated and set the simulation time (*h),* (usually one year) to run with MCS.
- *Step 2:* Generate uniform random numbers to obtain the stochastic failure/repair operation cycle for the system components.
- *Step 3:* Define the system capacity by aggregating the available capacities of all system components and defining the load level.
- *Step 4:* Select a system state (success state and failure state), by checking that the load level can be met by the available capacity (in case composite reliability using optimal power flow to assess the deficiency).
- *Step 5:* Evaluate and update the outcome of the test function for the reliability indices evaluation.
- *Step 6:* If *(N)* is equal to the maximum number of years, stop the simulation; otherwise set (*N=N+1), (h=0)*, and go back to Step 2 and repeat the attempt. Fig. 3 shows a flowchart of the main steps in reliability indices assessment.

A general observation of these steps shows that the MCS method takes a long time to estimate power systems reliability or evaluate reliability indices. This is because conventional MCS generates a series of numbers quite randomly in order to guarantee the probability distribution for the expected loss of demand. Many techniques have therefore been proposed to reduce the computational effort required to evaluate generating system reliability, composite system reliability and distribution system reliability. These techniques include:

1. VRTs [67–71]: methods based on Monte Carlo models that are implemented with VRTs to reduce computational effort;
2. Importance Sampling [72];
3. MCS and fuzzy algorithms: references [73–80,107] present an overview of the application of a fuzzy set to power system modeling;
4. Artificial neural networks: all types of reliability indices can be evaluated using these networks supplemented by MCS for composite system reliability [81–86,145];

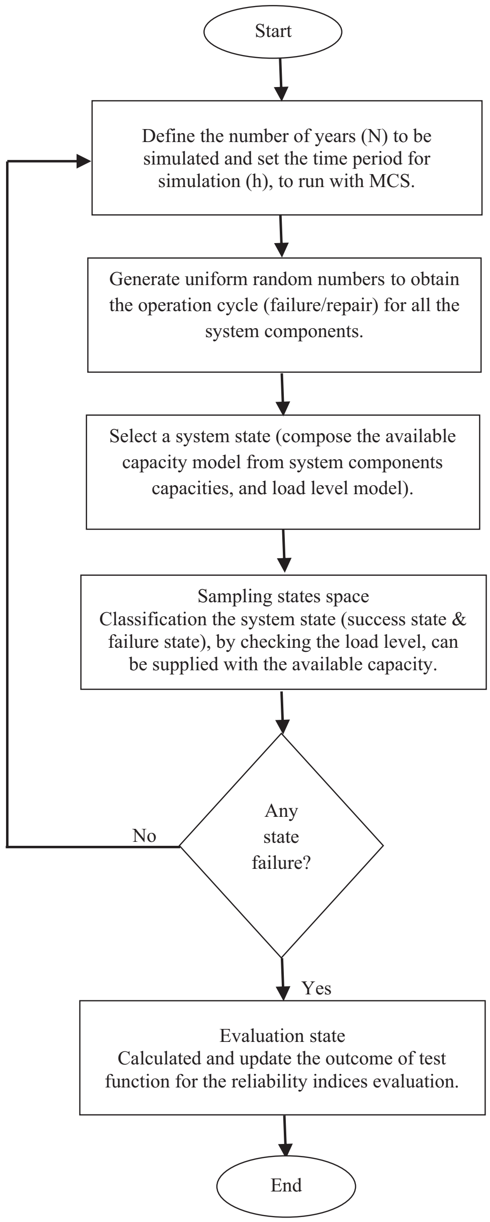

Fig. 3. Flowchart for the steps of the reliability assessment methodology.

5. Genetic algorithms: a method using for evaluating reliability indices for generating and generation and transmission systems [87–91].

Superior sampling efficiency and quality of MCS convergence are necessary if computational expenses are to be kept to a minimum [92]. This paper reviews several techniques for minimizing computation time and maintaining a high degree of estimate when assessing the reliability indices for generating systems. The following section describes the selected methodologies:

5.1. Monte Carlo Simulation (MCS)

Monte Carlo simulation (MCS) has been recently re-established, largely due to improved understanding of its capabilities, and sometimes because it is the only available technique [93]. The MCS method relies on statistics but is useful in various fields where statistical data is rare. When addressing problems that include random variables with given or known probability distributions, MCS.

results are presented in a histogram form which is especially useful for additional statistical assessments [6].

Table 1
Reliability evaluation indices vs number of samples using sequential MCS technique.

Refs.	Reliability indices	No of sample years				
Refs. [103]		2000	4000	6000	8000	10,000
	LOLE (h/yr.)	1.015	1.103	1.096	1.085	1.084
	LOEE (MWh/yr.)	8.257	9.833	10.263	10.106	9.908
	LOLF (occ/yr.)	0.21	0.22	0.22	0.21	0.21
	LOLLE (h/yr.)	1.010	1.102	1.090	1.075	1.161
Computed results	LOEE (MWh/yr.)	9.472	9.780	10.576	10.789	10.314
	LOLF (occ/yr.)	0.22	0.24	0.24	0.23	0.23
	Elapsed time (s)	6690.6	41985.21	37261.82	58124.17	95081.74

It should be noted that the sequential simulation method is a very comprehensive tool for evaluating reliability indices. Convergence criteria for MCS simulation algorithm are based on the variance of the recorded reliability indices. However, the major drawback of this method is the relatively high computational time required to converge variances for the reliability indices produced by this method. Many studies have used different models based on MCS, such as MCS-LSSVM [94], CREAM [68], MECORE [95], CONFTRA [96], and MOPSO [97]; and numerous works have also been proposed based on MCS to assess the reliability of power systems [98–100].

The sequential MCS approach is the most fundamental technique used to assess the adequacy of a power system [101,102]. In general, applying MCS first requires the appropriate computational resource to obtain sufficient accuracy in the actual results. Applying the sequential MCS technique on the Roy Billinton Test System [103], shows the relation between the computational effort of the simulation process and samples, as presented in Table 1.

Table 1 demonstrates that increasing the numbers of simulation to achieve the required degree of results in increased computation times, and the results have been compared with reference data [3]. Second, requires additional data in the form of distributions, along with conventional predicted values used in many analytical procedures [104].

The MCS method [105] has significant advantages when employed to assess power system reliability. Evaluating the reliability of power generation systems using probabilistic methods [106], has attracted considerable attention because of its capability to account for systematic uncertainties, particularly when used to evaluate the reliability indices of generating systems.

5.2. MCS with variance reduction techniques for reliability assessment

The computational effort required to gain an adequate degree of accuracy is the main limitation of Monte Carlo methods. Many studies have been proposed based on MCS and different VRTs for uncertainty variables in a generating system, such as energy prices and demand, which represent planning and operation tools in most generating systems [107,108]. MCS is more efficient in reducing computational time when VRTs are used. The aim of these techniques is to decrease the variance of the estimators of reliability indices with accurate values. Control variables (CV), antithetic variables (AV), and stratified sampling (SS) are some common techniques used to improve the precision and accuracy of estimator reliability indices in Refs. [109–111].

A computer algorithm has been designed that combines stratified sampling and antithetic sampling to enhance the accuracy of MCS

Table 2
Reliability indices calculate based on sequential MCS and VRTs techniques.

Refs.	VRTs methods used						Reliability indices			
	SMCS	Antithetic Variates (AV)	Control Variates (CV)	Dagger Sampling (DS)	Importance Sampling (IS)	Stratified sampling (SS)	LOLE (h/yr.)	EENS (MWh/yr.)	LOLF (ooc/yr.)	LOLP (h/yr.)
[47]	✓	✓				✓				
[48]	✓	✓						✓		✓
[49]	✓	✓	✓					✓	✓	✓
[53]	✓					✓				
[55]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
[56]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
[66]	✓				✓					
[67]	✓	✓			✓			✓		
[69]	✓				✓			✓		✓
[70]	✓				✓			✓		✓
[109]	✓	✓	✓					✓		✓
[110]	✓	✓				✓				
[111]	✓				✓			✓		✓
[137]	✓	✓	✓		✓			✓		✓
[71]	✓		✓		✓			✓		✓
[138]	✓				✓					

[47,48]. The major stimulus for using sequential MCS with variance reduction techniques is a reduction in the computational effort so that the results show a faster simulation process to realize the convergence [49]. Table 2 reviews of some of the applications used to study the reliability assessment by using non-sequential MCS and sequential MCS with different VRT techniques.

This paper also presents some studies focused on using the LHS method of reliability assessment that can yield the same quality of estimated reliability indices with fewer samples. As a result, variance reduction of reliability indices assessment can be achieved.

In the literature, LHS has been adopted in many power system applications as a variance reduction tool to evaluate generating system reliability [112,113], and reduce the required storage for simulation. LHS techniques are used to address the adequacy planning problem in a power system [114,115]. Moreover, some works have examined the impact of LHS on the reliability estimates of multi-area generation systems [116]. By applying LHS to different numerical examples, the results show that the computational time and required sample size to reach convergence can be further reduced [117,118].

Discrete LHS and LHS are two approaches employed to evaluate the reliability indices distribution of power systems with less associated consumption of memory [116]. The main advantage of this approach is its capability to perform naturally at any level of reliability analysis. LHS can produce the same quality of representativeness with a fewer number of samples. Consequently, a reduction in variance of the estimated indices can be achieved. In order to provide the reader with some references that have recently published, Table 3, reviews some studies of reliability assessment conducted using non-sequential MCS and sequential MCS with LHS techniques. In all cases, the results prove that LHS enhances the performance of MCS in the area of generation system reliability.

This paper also presents many works that have been successfully applied to various ranges of estimation and optimization problems [119–130]. In particular, importance sampling is used to estimate rare-event probabilities through the alternative CE method approach.

The CE approach is a general stochastic optimization technique for a good speed-up provides a considerable reduction in the number of samples required for convergence in which it aims to propose a new density or obtaining a new density at least very close to the original density distributions for the reliability indices. Selection a new density distribution different from the original distributions, according to this, the sample variance is minimized and the convergence is achieved. The efficiency of the CE depends on finding the new distributions or very close to it. New distributions lead to change the original distributions, therefore, the mean values for reliability indices which can obtain it with the CE, these values cannot be depended on it in compensated for the real distributions of the same reliability indices [52]. A general introduction to the CE method is provided in [60,62,131,132]. The CE approach is a general stochastic optimization technique for solving both discrete and continuous multi- objective optimization problems [133,134].

The numbers of the applications using the CE method have recently increased. Table 4 reviews of some of the applications studying reliability assessment by using non-sequential MCS, and sequential MCS with CE techniques. In real applications, computational performance and speed-up can be easily achieved using the CE method and IS to estimate the reliability indices of generating and composite systems [65,135]. A good speed-up provides a considerable reduction in the number of samples required for convergence in [136].

5.3. population-based intelligent search for Reliability Assessment

This paper also presents some studies focused on using the optimization techniques (enumeration algorithms) based on metaheur-

Table 3
Reliability indices calculate based on non-sequential and sequential MCS with LHS techniques.

Refs.	Methods used			Reliability indices				Time (s)	Test system
	NSMCS	SMCS	LHS	LOLF	LOLD	LOLP	EPNS		
[113]	✓	✓	✓			✓	✓	2508	IEEE RTS96
[115]	✓	✓	✓	✓	✓	✓	✓	Several cases	IEEE RTS79
[117]		✓	✓	✓	✓	✓	✓	1560	IEEE RTS79
[119]		✓	✓	✓	✓	✓	✓	Several cases	IEEE RTS79
[139]	✓		✓			✓		Several cases	IEEE RTS79

Table 4
Reliability indices calculate based on non-sequential MCS and sequential MCS with CE techniques.

Refs.	Methods used			Reliability indices					Time (s)	Test system
	NSMCS	SMCS	CE	LOLE	LOLF	LOLD	LOLP	EPNS		
[51]		✓	✓		✓		✓	✓	35.7	IEEE RTS79
[52]		✓	✓	✓	✓			✓	4.07	IEEE RTS96
[65]	✓	✓	✓	✓	✓			✓	86	IEEE RTS79–96
[71]		✓	✓				✓	✓	Several cases	IEEE RTS79–96
[132]		✓	✓	✓	✓			✓	Several cases	R-RBTS
[135]			✓				✓		Several cases	IEEE RTS79–96
[136]		✓	✓		✓		✓	✓	59	IEEE RTS79–96
[140]	✓	✓	✓				✓	✓	Several cases	IEEE RTS79
[141]		✓	✓	✓	✓			✓	Several cases	RBTS, IEEE RTS79
[142]		✓	✓						Several cases	IEEE RTS79
[143]		✓	✓	✓	✓	✓	✓	✓	Several cases	IEEE RTS96
[144]		✓	✓				✓	✓	Several cases	IEEE RTS79

Table 5
Reliability indices calculate based on Population-based intelligent search techniques.

Refs.	Population-based intelligent search techniques				Reliability indices			
	Genetic Algorithm (GA)	State space pruning (SSP)	Particle swarm optimization (PSO)	Others algorithms	LOLE (h/yr.)	EENS (MWh/yr.)	LOLF (Ac/yr.)	LOLP (h/yr.)
[35]			✓		✓	✓		✓
[46]			✓			✓	✓	✓
[63]		✓						✓
[119]				✓				
[145]				✓		✓	✓	✓
[146]		✓						✓
[86]	✓					✓		✓
[87]	✓							✓
[88]				✓	✓	✓	✓	✓
[147]		✓						✓
[148]		✓						✓
[73]	✓					✓	✓	✓
[90]	✓				✓	✓	✓	
[35]				✓	✓	✓	✓	
[149]	✓				✓	✓	✓	
[89]	✓				✓		✓	
[150]			✓		✓			
[151]				✓	✓	✓	✓	
[26]			✓		✓	✓	✓	✓
[152]	✓							✓
[153]				✓				✓
[154]			✓					✓
[155]			✓		✓	✓		✓

istic searching for the truncated sampling of state-space are proposed for reliability assessment of the power generation system adequacy. The objective of using metaheuristic optimization techniques is to present new algorithms that can solve complicated reliability analysis for electrical power systems, such as the increase in the complexity of the power systems infrastructure, low accuracy for reliability indices estimate, and large computation effort.

Both the MCS and PIS methods have the state spaces, but are different in their mechanisms for sampling; with regards to MCS, the state of success or failure influences the reliability indices estimation. This implies that the sampling of the state of failure is less likely compared to the state of success. This condition explains why the convergence takes more computation effort in the reliability assessment of highly reliable systems. Meanwhile, for the PIS, the system state of the failure probability system can guide the search [35]. Therefore, the state of a system that has a higher probability of failure can ensure greater chances to be nominated and evaluated. To date, this characteristic has enabled the PIS algorithms to be utilized to address reliability problems due to its higher efficiency. Table 5, reviews some studies of reliability assessment conducted using PIS techniques. The results indicated that the reliability indices derived from the use the PIS corresponded closely with those derived from the use of an analytical approach or Monte Carlo simulation with less computation burden.

6. Conclusion

A power system is a large and complex system; hence reliability assessment is also a complex process. For large networks, estimating reliability using simulation techniques is necessary. The computational effort required to gain a sufficient degree of accuracy is the main limitation of Monte Carlo methods. The number of samples required by the MCS method can be reduced using VRTs. The aim of these techniques is to decrease the estimate variance for reliability indices. Many studies have been proposed based on MCS and different VRTs. These techniques rely on information regarding the model of the system under consideration. A simulation that uses information collected a priori is more effective for reducing variance.

The MCS models, wherein estimations are conducted using a digital computer, offer a robust approach to evaluating system reliability. This study provides a brief introduction to MCS and several MCS based techniques combined with VRTs such as MCS–LHS, MCS–CE, and MCS–IS.

The outstanding of this paper utilizing sequential Monte Carlo simulation in reliability indices analysis needs the great computation effort, by employed the VRTs methods of reliability assessment that can yield the same quality of estimated reliability indices with fewer samples. As a result, variance reduction of reliability indices assessment can be achieved. By applying LHS to different numerical examples, the results show that the computational time and sample size to reach convergence can be further reduced. LHS can produce the same quality of representativeness with a fewer number of samples. Consequently, a reduction in variance of the estimated indices can be achieved. Also, the computational performance and speed-up for SMCS method can be easily achieved by using the CE method and IS to assess the generating adequacy and composite reliability of the power systems, by a considerable reduction in the number of samples and a good speed -up required for convergence. The efficiency of the CE depends on finding the new distributions or very close to it. The change of the original probability distributions is the weakness of this approach, therefore, the mean values for reliability indices which can obtain it with the CE, these values cannot depend on it in compensated for the real distributions of some reliability indices.

Finally, this study described and discussed reviewing some the generation reliability assessment methods for power systems using MCS and VRTS. The main objective of this work is to present efficient estimation and accurate methodologies based on a pattern simulation technique to minimize computational efforts significantly while evaluating generating reliability.

Also, the reviews indicated that the reliability indices derived from the use the PIS corresponded closely with those derived from the use of an analytical approach or Monte Carlo simulation but with reduced computational burden.

This paper also discussed the PIS which employed an optimization search tool for the reliability indices of power generating system and relies on the population-based intelligent search method, which is considered as a viable replacement for the analysis and Monte Carlo simulation in assessing non-chronological system reliability indices. In conclusion, the benefits of using the intelligent search techniques are that an accurate assessment of reliability indices for the power generation system with less computational effort can be obtained.

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