A Cross-Entropy-Based Three-Stage Sequential Importance Sampling for Composite Power System Short-Term Reliability Evaluation

Yue Wang, Chuangxin Guo, *Member, IEEE*, and Q. H. Wu, *Fellow, IEEE*

***Abstract*—Regarding short-term reliability of composite power system, probability of critical event resulting in system failure within a short lead time is extremely low, which renders classical sequential Monte Carlo simulation method inefficient. In this paper, a cross-entropy-based three-stage sequential importance sampling (TSSIS) method is proposed to solve the low efficiency problem resulted from the low rate of component state transition during a fixed lead time. First, by assuming the system state transition process conforms to continuous time Markov chain, an analytical solution to optimal distorted component state transition rate to be used for sequential importance sampling is found by means of cross-entropy method. Second, TSSIS for a fixed lead time is constructed as follows: 1) acceleration of producing system state transitions; 2) enhanced learning to give optimal distorted transition rate; 3) compensation to the cost function. Case studies based on a reinforced Roy Billinton reliability test system and RTS-79 are carried out respectively for illustration of parameter settings of TSSIS as well as efficiency gain in comparison with the classical sequential Monte Carlo simulation method. The results demonstrate that given rational setting of parameters, TSSIS is of relatively high efficiency for sequential short-term reliability evaluation of composite power system.**

***Index Terms*—Cross-entropy, importance sampling, risk assessment, sequential Monte Carlo, short-term reliability evaluation.**

NOMENCLATURE

CSMCS	Classical sequential Monte Carlo simulation.
CE	Cross-entropy.
CTMC	Continuous time Markov chain.
EENS	Expected energy not supplied.
LOLE	Lost of load expectation.
LOLD	Lost of load duration.
LOLF	Lost of load frequency.
MCS	Monte Carlo simulation.
PDF	Probability density function.
R-RBTS	Reinforced Roy Billinton reliability test system.
TSSIS	Cross-entropy-based three-stage sequential importance sampling.
T_{L}	Lead time.
K	Number of components.
Γ	State transition path of continuous time Markov chain within T_{L}.
m	Number of state transitions in Γ.
$f(\Gamma)$	Conditional likelihood of Γ conditioned on m.
$S(\Gamma)$	Real-valued cost as function of Γ.
$S_{\mathrm{I}}(\Gamma)$	Defined cost as function of Γ in Stage One of TSSIS.
N_1	Total number of sample realization in Stage One of TSSIS.
$S_{\mathrm{II}}(\Gamma)$	Defined cost as function of Γ in Stage Two of TSSIS.
N_2	Total number of sample realization in Stage Two of TSSIS.
$\boldsymbol{\eta}$	Set of original component transition rates.
Ef	Efficiency gain.
σ	Coefficient of variance.

Manuscript received October 31, 2012; revised February 05, 2013, April 19, 2013, and June 07, 2013; accepted July 21, 2013. Date of publication August 21, 2013; date of current version October 17, 2013. This work was supported by the National Science Foundation (51177143), 973 Program of China (2013CB228206) and Zhejiang Provincial Natural Science Foundation (Y1100243 and LZ12E07002). Paper no. TPWRS-01218-2012.

Y. Wang and C. Guo are with the College of Electrical Engineering, Zhejiang University, Hangzhou, Zhejiang Province, China (e-mail: guochuangxin@zju.edu.cn).

Q. H. Wu is with the Department of Electrical Engineering and Electronics, The University of Liverpool, Liverpool, L69 3GJ, U.K.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TPWRS.2013.2276001

I. INTRODUCTION

MODERN power systems are experiencing a worldwide trend of deregulation in the light of energy crisis and environmental issues. Electric power utilities are faced with great challenges to balance trade off between investment profits and operational reliability. In lack of unified regulations, present operational strategies formulated to represent individual interests will undoubtedly drive power systems further to or even beyond operating limits [1]. Both independent system organizers and electric power entities need to be adequately aware of system operating pressures during a short interval in the future in a precise and uninterrupted manner, which could be achieved by employing short-term reliability evaluation techniques for composite power systems.

The short-term reliability evaluation for a composite power system can measure the ability of the whole system to withstand unexpected interruptions resulted from imminent probabilistic disturbances to both the generation and the transmission subsystems within a short span in the near future, so-called lead time. Distinct from short-term generation capacity evaluation [2]–[6] used to assess spinning reserve of a fleet of generators, transmission system contingencies should be additionally taken into account in composite short-term reliability evaluation. In addition, the effects of remedial actions, such as load shedding, transformer tap changing and/or re-dispatching generator outputs, on estimation of reliability indices can not be neglected. Generally, composite system reliability evaluation can be classified into adequacy analysis and security analysis depending on the primary aspect of concern in case of a contingency. In the adequacy evaluation which we pay attention to, we should investigate whether there exist enough both sufficient generation capacity for the energy demand and the associated transmission facilities required to transmit energy to major system load points [7]. It is conventionally assumed that a disturbed system can automatically recover or be manually restored to be stable, that is to say, such dynamic responses as time-dependent bus voltage collapse and generator rotor angle instability, would not be considered after a disturbance, and remedial actions can be, if needed, thereof effectively conducted to bring the abnormal state back into a new equilibrium operating point. Due to the short time scale considered in the short-term reliability evaluation, such events as scheduled outages, deratings, planned maintenance, and postponed failures should not be considered [3]. Moreover, the forecasted load level could be considered as constant, or random but complying with a certain distribution [7], e.g., Gaussian distribution. In addition, the failure rate of a component is not a steady-state value as used in long-term evaluation, but a function of the environment it is exposed to [8], for instance, the failure rate of an overhead transmission line can be much higher in adverse climatic conditions than that in fair ones. The time-specific or environment-dependent system operating pressure can be reflected by reliability indices released by short-term composite adequacy evaluation. This information is useful to assist power system operators in decision making to timely avoid hazard event such as cascading outage [9], or in reward/penalty analysis [1].

The methodologies used for the short-term reliability evaluation of composite power system have been studied in [8]–[12]. As the volume of possible operational states of composite power system is huge, the Monte Carlo simulation (MCS) method [9]–[12] is much more preferred in terms of its advantage of easy implementation, ergodicity and robustness to the dimension of the problem compared with analytical methods [8]. There exist two well-known frameworks of MCS methods, namely sequential MCS method and nonsequential MCS method. One important advantage of sequential MCS method over the others is that the chronological probabilistic nature of system behavior and component failures can be simulated sequentially, as a result, indices relevant to state duration, e.g., failure cost as a function of state duration, loss of load duration (LOLD) and loss of load expectation (LOLE), etc., can be calculated directly and unbiased results are obtained. However, since a contingency of composite power system, such as load shedding, is often triggered by several components failing together within a relatively short lead time, the probability of such event is extremely low with respect to modern highly reliable components. For instance, it is a common practice to assume the time to failure of a component to be exponentially distributed, and annual average failure rates are commonly of magnitudes between 10^{-2}/yr and 10/yr in normal operating conditions, whereas, in short-term reliability evaluation, between 10^{-6}/h and 10^{-2}/h or even lower when only several hours considered. That is, in average a single component may fail one time over 10^{6} hrs such that it is very difficult for the CSMCS method to sample sufficient failure events in a short lead time. The simulation efficiency decreases consequently. From this point of view, it is meaningful to develop an effective algorithm to improve the CSMCS method for short-term reliability evaluation.

Various researches endeavoring to improve CSMCS efficiency for power system reliability evaluation have been reported. Reference [13] contributed by reducing time consumption for contingency loss calculation associated with each sampled state.

A pseudo-chronological MCS tool [14] was proposed to overcome computational burden of the CSMCS method. Recently, an algorithm for reliability simulation of equipment and systems using a parallel computing environment based on the CSMCS framework has been developed [15]. It improves the efficiency by sampling states sequences in parallel, however, it requires huge hardware support once state transition rate is extremely low.

The efficiency of the CSMCS method in generating capacity reliability evaluation has been prominently improved [6] on the basis of cross-entropy (CE) technique [16], [17]. It is achieved through iterative selection, in low generation capacity, of sampled system states which are used for optimal distortion of component failure rate. As a result, system failure events, such as deficit of energy, can be effectively sampled with the optimal distorted failure rate. The same concept can be employed in sequential composite short-term reliability evaluation. However, in the light of transmission system constraints, selection of the best sampled system sequences used for component state transition rate optimization is not so straightforward because it is determined by both generation capacity and transmission capacity combined with system load level. On the other hand, identification of a failure event usually involves time-consuming remedial action analysis including power flow and or optimal power flow analysis, thus, a huge volume of sampled system states should be avoided as much as possible to ensure evaluation efficiency.

Inspired by [6], [16], and [17] in this paper, a novel cross-entropy-based three-stage sequential importance sampling (TSSIS) method is proposed to improve sequential composite short-term reliability evaluation within a fixed lead time confronted with relatively low component state transition rate. First, by assuming the system state transition process conforms to continuous time Markov chain (CTMC), an optimal distorted component state transition rate used for sequential importance sampling within a fixed lead time is derived by minimizing the

Kullback-Leibler distance between the zero-variance probability density function (PDF) and a parametric PDF. A method is proposed to solve the optimal distorted transition rate based on which the short-term likelihood ratio compensator for importance sampling is derived. The proposed TSSIS procedure as a whole consists of three distinct stages. At the first stage, the generation of sequential transition path leading to system failure is accelerated; At the second stage, enhanced learning for optimal component state transition rate for sequential importance sampling is conducted by utilizing the samples obtained from the first stage; At the last stage, the distorted sequential transition path is simulated, resulting in a pre-defined cost which is compensated according to the short-term likelihood ratio compensator. In the final section of the paper, we explain parameter settings of the proposed method through case studies on a reinforced Roy Billinton reliability test system [18] along with efficiency gain in comparison with the CSMCS method through tests on RTS-79 [19].

II. Classical Sequential MCS Within Fixed Lead Time

A system state transition sampling method proposed in [20] is utilized in this paper to develop the proposed TSSIS method. Simulation philosophy is briefly reviewed as follows: Given a multi-state system complying with CTMC assumption and provided there is no absorbing state, let Ω denote its state space, $\Omega_x \subseteq \Omega$ is a subset space in which each state is associated with x by one-step transition. Obviously, cardinality of Ω_x satisfies $\mathrm{Card}(\Omega_x) \geq 1$. Denote $y \in \Omega$, then the probability of one-step transition from x to y within a fixed time interval $\triangle t$ can be expressed as follows [20]:

$$P_{x,y} = \begin{cases} \dfrac{\lambda_{x,y}}{\lambda_x}\left(1 - e^{-\lambda_x \triangle t}\right), & y \in \Omega_x \\ 0, & y \notin \Omega_x \end{cases} \tag{1}$$

where $\lambda_{x,y}$ represents transition rate from x to y, $\lambda_x = \sum_{k \in \Omega_x} \lambda_{x,k}$ represents transition rate of departing out of x which is sum of transition rates from x to any other states in Ω_x.

If we assign each state in Ω a natural number, and let (x_i, t_i) represent a visited state x_i at time t_i, $t_i < t_{i+1}$, $i = 0, 1, 2, \ldots$, then, as shown in Fig. 1, starting from an original state (x_0, t_0), a sequential transition path within a fixed time interval can be denoted by: $\Gamma = \{(x_0, t_0), (x_1, t_1), (x_m, t_m), (x_m, t_0 + T_{\mathrm{L}})\}$ with T_{L} denoted as time span. The last term $(x_m, t_0 + T_{\mathrm{L}})$ means that once sampled (x_{m+1}, t_{m+1}) goes beyond $t_0 + T_{\mathrm{L}}$, only the transition time span $T_{\mathrm{L}} + t_0 - t_m$ for the state x_m is considered into likelihood irrespective of the visited state x_{m+1}. Based on the above conditions, likelihood for the sampled Γ [21] can be expressed as follows:

$$\begin{aligned} f(\Gamma) &= [1 - P_{x_m}(\triangle t_m)] \prod_{i=0}^{m-1} \frac{\mathrm{d}P_{x_i, x_{i+1}}}{\mathrm{d} \triangle t} \\ &= e^{-\lambda_{x_m} \triangle t_m} \prod_{i=0}^{m-1} \lambda_{x_i, x_{i+1}} e^{-\lambda_{x_i} \triangle t_i} \end{aligned} \tag{2}$$

where $P_x(t)$ represents the probability of departure of state x within t, $\triangle t_i = t_{i+1} - t_i$ for $0 \leq i < m$ and $\triangle t_m = T_{\mathrm{L}} + t_0 - t_m$.

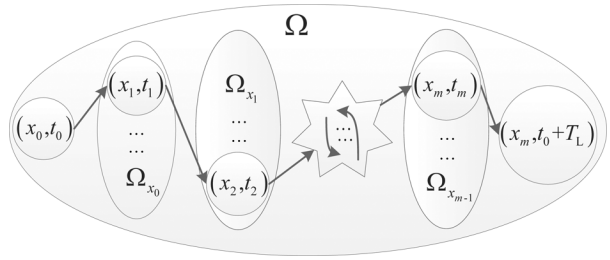


Fig. 1. Formation of a sequential transition path.

According to (1) and (2), the sequential simulation steps based on the system state transition sampling method to form Γ can be constructed as follows:

1) Given the present state x_i, find all the states associated with x_i by one-step transition to form Ω_{x_i} and denote the states in Ω_{x_i} by $\{y_{i1}, y_{i2}, \ldots, y_{iZ}\}$ where Z represents the cardinality of Ω_{x_i}. Then, the steps of selecting the next visited state x_{i+1} from Ω_{x_i} are as follows: if $\mathrm{Card}(\Omega_{x_i}) = 1$, then there is no need of additional calculations as y_{i1} is the only possible state to be visited, i.e., $x_{i+1} = y_{i1}$; otherwise, randomly produce a number, a, from the uniform distribution defined on $[0, 1)$ to determine the next state, $x_{i+1} = y_{iz}$, where natural number z is determined by the following equation:

$$\begin{cases} \displaystyle\sum_{k=1}^{z-1} \frac{\lambda_{x_i, y_{ik}}}{\lambda_{x_i}} \leq a < \sum_{k=1}^{z} \frac{\lambda_{x_i, y_{ik}}}{\lambda_{x_i}}, & z \geq 2 \\ a < \frac{\lambda_{x_i, y_{i1}}}{\lambda_{x_i}}, & z = 1 \end{cases} \quad \text{for } i = 0, 1, \ldots, m-1. \tag{3}$$

2) Once again produce a random number, q, from the uniform distribution defined on $(0, 1)$, then the sojourn time of x_i is determined by

$$\triangle t_i = \begin{cases} -\dfrac{\ln q}{\lambda_i}, & 0 \leq i < m \\ T_{\mathrm{L}} + t_0 - t_m, & i = m. \end{cases} \tag{4}$$

3) Calculate the one-step transition cost which is a defined function of x_i, x_{i+1} and $\triangle t_i$. The cost may be energy not supplied, economic loss or outage duration for instance.
4) Repeat 1)–3) until $\sum_{i=0}^{m} \triangle t_i = T_{\mathrm{L}}$ is satisfied, then, add all of the one-step transition costs to form a total cost of the sequential transition path.
5) Repeat 1)–4) until the coefficient of variation [22] or a predefined size of pool of sequential transition path costs is satisfied.

III. Cross-Entropy-Based Three-Stage Sequential Importance Sampling Method

This section first introduces basic idea of CE, then followed by the analytical solution to the optimal distorted transition rate used for sequential importance sampling simulation method within a fixed lead time. The transition rates to be distorted are in fact parameters of the PDF of sequential transition path which is selected out from a parametric family from which the perfect zero-variance PDF comes. The parametric PDF has a

merit of not influencing the system original CTMC characteristics. Based on this parametric PDF, in Section III-C, it will be seen that the derived analytical solution is very convenient to be embedded into the traditional CE-based sampling simulation procedure [16], [17] to form the TSSIS method.

A. Basic Idea on CE-Based Importance Sampling

First, the zero-variance PDF for the importance sampling simulation method applied to general problems can be expressed as:

$$h(x;\boldsymbol{\alpha}) = g(x;\boldsymbol{\beta})\frac{S(x)}{E_g[S(x)]} \tag{5}$$

where $h(x;\boldsymbol{\alpha})$ is the zero-variance PDF, x is a random variable, $\boldsymbol{\alpha}$ is a vector of parameters, $g(x;\boldsymbol{\beta})$ is the original problem-specific PDF and $\boldsymbol{\beta}$ is the corresponding original parameter vector. $S(x)$ denotes a real-valued function of x, such as energy not supplied. $E_g(\cdot)$ represents the expected quantity to be estimated under $g(x;\boldsymbol{\beta})$. From (5), it can be noted that if $h(x;\boldsymbol{\alpha})$ is given, we need nothing but only one simulation to get $E_g[S(x)]$; however, the exact $h(x;\boldsymbol{\alpha})$ cannot be known before simulation. Obviously, $h(x;\boldsymbol{\alpha})$ and $E_g[S(x)]$ is a pair of interdependent variables, and an efficient way to decouple the interdependence is to estimate $h(x;\boldsymbol{\alpha})$ preliminarily, and simulate $E_g(\cdot)$ to iteratively update $h(x;\boldsymbol{\alpha})$.

The CE method is a kind of stochastic simulation method with iterative sample learning. The basic idea of CE is to find a surrogate PDF for $h(x;\boldsymbol{\alpha})$ by minimizing the Kullback-Leibler distance between zero-variance PDF and a parametric PDF with the same family as $g(x;\boldsymbol{\beta})$. Compared with other metrics quantifying the distance between the two PDFs [23], CE is more applicable to deal with the exponential distribution family.

Let $g(x;\boldsymbol{\alpha}')$ represent a PDF stemming from the same distribution family from which $g(x;\boldsymbol{\beta})$ comes, then, the parameter vector $\boldsymbol{\alpha}'$ can be iteratively obtained as (6) by minimizing the Kullback-Leibler distance between $g(x;\boldsymbol{\alpha}')$ and $h(x;\boldsymbol{\alpha})$ [16], [17]:

$$\boldsymbol{\alpha}'^{(n+1)} = \arg\max_{\boldsymbol{\alpha}'}\left[\frac{1}{N}\sum\nolimits_{i=1}^{N} S\left(x_i^{(n)}\right)\frac{g\left(x_i^{(n)};\boldsymbol{\beta}\right)}{g\left(x_i^{(n)};\boldsymbol{\alpha}'^{(n)}\right)} \times \ln g\left(x_i^{(n)};\boldsymbol{\alpha}'\right)\right] \tag{6}$$

where the superscript (n) denotes number of the iterations, $\boldsymbol{\alpha}'^{(n)}$ is an iteratively distorted parameter vector of $\boldsymbol{\beta}$ and generally $\boldsymbol{\alpha}'^{(1)} \equiv \boldsymbol{\beta}$, N is a pre-defined total number of simulations, and $x_i^{(n)}$ is a sample from $g(x;\boldsymbol{\alpha}'^{(n)})$. In most of practical problems, $S(\cdot) \geq 0$, thus, as long as $\ln g(x;\boldsymbol{\alpha}')$ is convex and differentiable with respect to $\boldsymbol{\alpha}'$, the problem of solving (6) will equivalently be reduced to solve the following (7):

$$\sum_{i=1}^{N} S\left(x_i^{(n)}\right)\frac{g\left(x_i^{(n)};\boldsymbol{\beta}\right)}{g\left(x_i^{(n)};\boldsymbol{\alpha}'^{(n)}\right)}\frac{\partial \ln g\left(x_i^{(n)};\boldsymbol{\alpha}'\right)}{\partial \boldsymbol{\alpha}'} = 0. \tag{7}$$

The nth iterative solution to (7) is just the general estimator for optimal distorted parameters of PDF from the viewpoint of CE. In common practices, $n = 5$ may be adequate.

B. Optimal Distorted State Transition Rate From CE Perspective

Considering a multi-state Markov system, the system state $x = [\theta_1, \ldots \theta_k]$ can be adequately determined by a combination of states of its components θ_c, $c = 1, \ldots K$, where K is the number of components and $\theta_c \in \{0, 1, 2 \ldots M\}$ represents a state level of component c, and specifically, level 0 represents total loss of function and M represents normal operation, and the other numbers between 0 and M represent intermediate states respectively. Take a transmission line with two Markov states for instance, $\theta_c = 1$ represents the operating (up) state and $\theta_c = 0$ otherwise. The state transition rate of component c is denoted as η_θ^c, which is determined by the state θ of the component in system state x, specifically, if $\theta = 1$, η_θ^c represents failure rate, otherwise, repair rate.

Given components operate mutually independently and simultaneous failures of two or more components are neglected, and given two-state Markov model for each component for simplicity, system state transition $\ell_{x\to y}^c$ from x to y is totally determined by component c, which leads the transition by changing its own up or down state in x to the other in y while leaving other component states unchanged. Therefore, the system state transition rate $\lambda_{x_i,x_{i+1}}$ in (2) is equal to the leading component transition rate $\eta_{x_i}^c$ at the ith transition where $\eta_{x_i}^c = \eta_\theta^c$ and θ is determined by the component state in x_i, hence $\lambda_{x_i} = \sum_{c=1}^{k} \eta_{x_i}^c$. We denote the system state transition rate of x_i by $\eta_{x_i}^s := \lambda_{x_i}$ for clarity. Given these conditions, we can get the likelihood of system sequential transition path for a fixed time interval from (2) as (8):

$$f(\Gamma;\boldsymbol{\eta},m) = e^{-\eta_{x_m}^s \triangle t_m}\prod_{i=0}^{m-1}\eta_{x_i}^c e^{-\eta_{x_i}^s \triangle t_i}. \tag{8}$$

Herein, it is worth underlining that (8) can be regarded as a conditional likelihood of Γ conditioned on a given m. Provided $m \sim P_m(\cdot)$ where $P_m(\cdot)$ represents the probability mass function of m. Then, the full PDF of Γ within the time interval can be expressed as $g(\Gamma;\boldsymbol{\beta}) = \sum_{i=1}^{\infty} f(\Gamma;\boldsymbol{\eta},i)P_m(i)$. Every drawn Γ_i definitely yields m_i, by employing the system state transition sampling method. Then

$$g(\Gamma_i;\boldsymbol{\beta}) = f(\Gamma_i;\boldsymbol{\eta},m_i)P_m(m_i). \tag{9}$$

If m_i is not to be distorted, let $\boldsymbol{\eta}^{(n)}$ represent the nth iteratively distorted version of $\boldsymbol{\eta}$, then substituting (9) into (7) results in

$$\sum_{i=1}^{N} S\left(\Gamma_i^{(n)}\right)\frac{f\left(\Gamma_i^{(n)};\boldsymbol{\eta},m\right)}{f\left(\Gamma_i^{(n)};\boldsymbol{\eta}^{(n)},m\right)} \times \frac{\partial \ln f\left(\Gamma_i^{(n)};\boldsymbol{\eta}^{(n+1)},m\right)}{\partial \boldsymbol{\eta}^{(n+1)}} = 0. \tag{10}$$

Bearing in mind that Γ_i can be simulated with the system state transition sampling method and m is readily known, thus,

in the following parts, m will not be explicitly written in $f(\cdot)$ for conciseness.

By substituting (8) into (10), the iterative estimator for CE-based distorted transition rate η_θ^c can be derived as

$$\eta_\theta^{c,(n+1)} = \frac{\sum_{i=1}^{N} S\left(\Gamma_i^{(n)}\right) \frac{f\left(\Gamma_i^{(n)};\boldsymbol{\eta}^{(1)}\right)}{f\left(\Gamma_i^{(n)};\boldsymbol{\eta}^{(n)}\right)} b_{ic}^{(n)}}{\sum_{i=1}^{N} S\left(\Gamma_i^{(n)}\right) \frac{f\left(\Gamma_i^{(n)};\boldsymbol{\eta}^{(1)}\right)}{f\left(\Gamma_i^{(n)};\boldsymbol{\eta}^{(n)}\right)} d_{ic}^{(n)}} \tag{11}$$

where $b_{ic}^{(n)}$ and $d_{ic}^{(n)}$ are respectively total occurrence times of $\eta_\theta^{c,(n+1)}$ and amount of sojourn span of system states whose transition rates are partially contributed by $\eta_\theta^{c,(n+1)}$ in $\Gamma_i^{(n)}$, and the elements of $\boldsymbol{\eta}^{(1)}$ is assigned to original transition rates of components.

C. Proposed Simulation Procedure

When simulating the expected cost of sequential transition path in a multi-state highly reliable system, generally $1/\eta_{x_0}^s \gg T_{\mathrm{L}}$ results that $S(\Gamma_i) > 0$, e.g., energy not supplied, is a rare contingency event as mentioned in the Introduction. Consequently, it is rather time-consuming to obtain enough sequential transition paths to update $\boldsymbol{\eta}^{(2)}$ in terms of (11). One could argue that the Γ_i associated with low generating capacity will be used to update $\boldsymbol{\eta}^{(2)}$, however, it has been found in [26] that, the importance sampling efficiency and robust is essentially related to the likelihood of each sampled sequential transition path which in our concerned problem is determined by both generation capacity and transmission lines in composite power system. It is obvious that if a certain group of sequential transition paths, e.g., generation state transition without transmission line state transition or the reverse, are inordinately preferred, the system transition path could be overbiased, consequently, the resulting expected value of concern will be unavoidably smaller than the real value unless a huge number of sequential transition paths are sampled which however must be avoided in complex composite power system. From this point of view, the TSSIS method is devised as follows:

First, define a first-stage cost function $S_{\mathrm{I}}(\Gamma; R)$ as (12)

$$S_{\mathrm{I}}(\Gamma; R) = \begin{cases} NC(\Gamma), & NC(\Gamma) \geq R \\ 0, & NC(\Gamma) < R \end{cases} \tag{12}$$

where $R = 1, 2, \ldots$ is a preset integer, and $NC(\Gamma)$ is the maximum number of components failing together in Γ. $S_{\mathrm{I}}(\Gamma; R)$ means that we first select simulation goal to select the Γ_{I} with at least R components failing together in $(0, T_{\mathrm{L}}]$. In another word, the first stage of the TSSIS method is meant to prefer the sequential transition path with more components failing in a short lead time, whereas importance measurement is not conducted on any component to avoid the above-mentioned inordinate favor in the case that no prior knowledge about the system is given. Afterwards, the Γ_{I} combined with (11) can be used to estimate the first-stage distorted transition rate $\boldsymbol{\eta}_{\mathrm{I}}$ which after several iterations can be utilized in subsequent stage to produce Γ_{II} resulting in higher likelihood of $S_{\mathrm{II}}(\Gamma_{\mathrm{II}}) > 0$ where $S_{\mathrm{II}}(\cdot)$ is

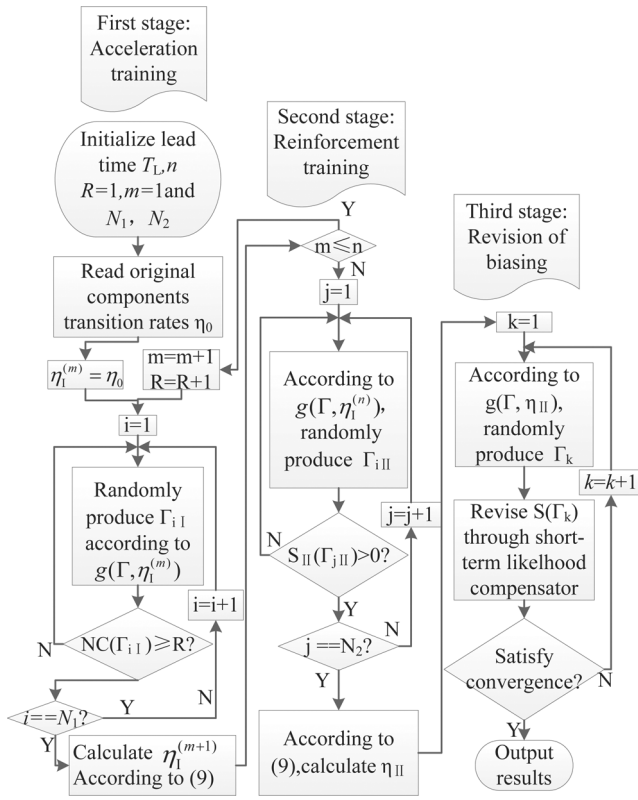


Fig. 2. Flow chart of the TSSIS method.

a defined real-valued cost function. At the second stage, traditional CE method is utilized to deliver the parameter $\boldsymbol{\eta}_{\mathrm{II}}$ according to $S_{\mathrm{II}}(\Gamma_{\mathrm{II}})$. At the last stage, the desired $E_g(S(x))$ is given by sampling Γ_i from $f(\Gamma; \boldsymbol{\eta}_{\mathrm{II}})$ to compute $S(\Gamma_i)$ which is then multiplied by short-term likelihood ratio compensator referring to (8). A complete flowchart of the TSSIS algorithm is shown in Fig. 2 and each step is explained exhaustively as follows:

First Stage: Accelerated generation of sequential transition path

1) Assign T_{L} as lead time, initiate $R = 1$, first-stage sampling number N_1, iteration number n and smoothing factor $\alpha = 0.1$. Read original transition rate vector $\boldsymbol{\eta}_0$. Let $j = 1$, $\boldsymbol{\eta}_{\mathrm{I}}^{(j)} \equiv \boldsymbol{\eta}_0$.

2) According to $f(\Gamma; \boldsymbol{\eta}_{\mathrm{I}}^{(j)})$, randomly produce N_1 samples of $\Gamma_{i\mathrm{I}}$ via the system state transition sampling method, $i = 1, \ldots, N_1$, calculate $S_{\mathrm{I}}(\Gamma_{i\mathrm{I}}; R)$ and $\boldsymbol{\eta}_{\mathrm{I}}^{(j+1)}$ according to (11). Update $\boldsymbol{\eta}_{\mathrm{I}}^{(j+1)} := \boldsymbol{\eta}_{\mathrm{I}}^{(j)}\alpha + \boldsymbol{\eta}_{\mathrm{I}}^{(j+1)}(1-\alpha)$, $j := j+1$ and $R := R + 1$. If $j < n$, repeat step 2).

Second Stage: Enhanced learning of sequential transition path

3) Set the number of simulation N_2 for the second stage.

4) According to $f(\Gamma; \boldsymbol{\eta}_{\mathrm{I}}^{(n)})$, randomly produce and gather N_2 samples of $\Gamma_{i\mathrm{II}}$ satisfying $S_{\mathrm{II}}(\Gamma_{i\mathrm{II}}) > 0$, $i = 1, \ldots, N_2$, then, $\boldsymbol{\eta}_{\mathrm{II}}$ is calculated according to (11).

Third Stage: Revision of biased cost of sequential transition path under sampling simulation

5) According to $f(\Gamma; \boldsymbol{\eta}_{\mathrm{II}})$, randomly produce set of distorted sequential transition paths and revise each $S(\Gamma_i)$

with a short-term likelihood ratio compensator defined as (13) to compose a set denoted by $\Lambda = \{S'(\Gamma_i), i = 1, 2, \ldots\}$, until the convergence condition associated with Λ is satisfied.

$$S'(\Gamma_i) = S(\Gamma_i)\frac{f(\Gamma_i;\boldsymbol{\eta}_0)}{f\left(\Gamma_i;\boldsymbol{\eta}_{\mathrm{II}}^{(n)}\right)}. \tag{13}$$

IV. Numerical Results

In this section, parameter settings for the TSSIS method and its efficiency in comparison with the CSMCS method are respectively studied by calculating EENS, LOLE and LOLF [7]. It is worth noting that there is a diversity of denotations for $S_{\mathrm{II}}(\cdot)$. In order to study the parameter settings, we first denote $S_{\mathrm{II}}(\Gamma)$ as a consequent cost of Γ, which is the energy not supplied within the corresponding lead time. A small test system is utilized to investigate impacts of critical parameter settings of the TSSIS method on its efficiency in Section IV-A, afterwards, performance studies with different detonations for $S_{\mathrm{II}}(\cdot)$ are carried out on RTS-79 in Section IV-B in comparison with the CSMCS method.

All calculations are conducted with MATLAB 2010b operating in the PC environment of AMD Athlon II X4 640 at 3.00 GHz. AC power flow and AC optimal power flow based on the Matpower are utilized to compute the indices. Considering the impacts of algorithm, rated operating constraint of components, coding platform as well as hardware conditions on simulation performance, a direct comparison of CPU times between the two different methods is rather difficult that we use the ratio of figures of merit [24] of the CSMCS method against the TSSIS with respect to the number of simulation runs to illustrate efficiency gain of the TSSIS method. The ratio of figures of merit denoted by Ef is computed by (14):

$$Ef = \frac{t_{\mathrm{c}}\sigma_{\mathrm{c}}^2}{t_{\mathrm{TS}}\sigma_{\mathrm{TS}}^2} \tag{14}$$

where t_{c} and t_{TS} are CPU times and σ_{c} and σ_{TS} are variances of reliability indices under the CSMCS method and the TSSIS method respectively. For the sake of impartial comparison, each of the following results is obtained by averaging 10 replicas under exactly same setting of conditions.

A. R-RBTS

A reinforced Roy Billinton reliability test system (R-RBTS) [18] is utilized for analysis in this subsection. The system consists of six buses connected by ten lines. System peak load is 185 MW with a total generation capacity of 240 MW. Failure and repair rate as well as operating constraints associated with each component can be found in [25]. The lead time studied is set to one hour.

We will investigate settings of the three critical parameters, n, N_1, N_2 by applying the TSSIS method to different scenarios of R-RBTS. It is worth mentioning that the first stage simulation, even with several iterations ($n > 1$), consumes trivial time (at second level) compared with the subsequent two stages (at minute level). Thanks to this feature, a large N_1 can be designated with regard to the number of system components to secure

TABLE I
Simulated Indices and CPU Times With Different Values of N_1 Under Conditions of $N_2 = 3000$ and $n = 3$ Under Peak Load for R-RBTS

N_1	EENS (MWh)	LOLE (hrs)	LOLF (occ./h)	CPU time (min)
100	2.2334×10^{-3}	1.8749×10^{-4}	3.8740×10^{-4}	25.33
500	2.5659×10^{-3}	2.1028×10^{-4}	4.3380×10^{-4}	29.56
1000	2.6319×10^{-3}	2.3347×10^{-4}	4.7479×10^{-4}	26.88
3000	2.6571×10^{-3}	2.2175×10^{-4}	4.5193×10^{-4}	28.11

TABLE II
Simulated Indices and CPU Times With Different Values of N_2 Under Conditions of $N_1 = 10\,000$ and $n = 3$ Under Peak Load for R-RBTS

N_2	EENS (MWh)	LOLE (hrs)	LOLF (occ./h)	CPU time (min)
$\leq$100		Fail		
200	2.5955×10^{-3}	2.1186×10^{-4}	4.4693×10^{-4}	12.2
300	2.4448×10^{-3}	2.094×10^{-4}	4.3565×10^{-4}	12.6
500	2.588×10^{-3}	2.2236×10^{-4}	4.4495×10^{-4}	16.20

that N_2 can be otherwise set as small as possible so as to reduce the simulation cost at the second stage, considering failure state analysis is relatively time-consuming; in the meanwhile, the inordinate favor must not be triggered.

Accordingly, we first investigate the relation between N_1 and inordinate favor by assigning N_2 with a sufficiently large value. Given a fixed coefficient of variance denoted by σ of an index, the inordinate favor is triggered when the simulated index is less than its real value. Table I lists the simulated indices and CPU times with different settings of N_1. The stop criterion for the third-stage simulation of the TSSIS method is $\sigma_{\mathrm{EENS}} \leq 0.05$. The other conditions for these experiments are: N_2 set to 3000, $n = 3$ and the load level at 185 MW. It is clearly shown in Table I that when $N_1 = 100$, the indices are the smallest and the CPU time the lowest. The reason can be given as follows: small N_1 implicitly favors a small portion of paths stochastically at the first stage, which are further optimized at the second stage. As a result, the condition of $\sigma \leq 0.05$ is satisfied without ergodically sampling all the possible paths with relative high probabilities leading to system failures at the third stage. That is why we should not solely select those sampled paths by lower generation capacity without consideration of transmission line constraints or the reverse. Obviously, the larger N_1 is, the more likely inordinate favor could be avoided. In this scenario the safe setting is $N_1 = 1000$.

From Table I, it can be also noted that the CPU time changes lightly with respect to N_1, however, according to the following tests, it is not the case with respect to N_2. With different values assigned to N_2, Table II shows the effect of N2 on CPU time, while setting $n = 3$ and $N_1 = 10\,000$ for the purpose of eliminating the impact of N_1. When N_2 is too small (≤ 100), the third-stage simulations in most of the replicated experiments are found to incur time-consuming convergence of the indices, which we regard as "Fail"($\mathrm{CPU\ time} > 30$ min). It should also be noted that $N_2 = 500$ is credibly adequate in this scenario. From Tables I and II, it is interesting to find that inordinate favor is primarily caused by N_1 and difficult convergence by N_2. Moreover, a larger value of N_2 resulting in considerable time-consuming is unnecessary. Therefore, the values of N_1 and N_2 need to be carefully chosen to achieve high efficiency. Ac-

TABLE III
RESULTS UNDER THE TSSIS METHOD APPLIED ON R-RBTS WITH DIFFERENT VALUES OF n AND LOAD LEVELS. $N_1 = 1260$, $N_2 = 420$

iteration	CPU time (sec)		
	185(MW)	166.5(MW)(90%)	148(MW)(80%)
n=0	8248.76	9659.05	Fail
n=1	**454.77**	**319.35**	2687.67
n=2	499.26	924.12	**2131.28**
n=3	603	650.26	4835.68
EENS(MWh)	2.6533×10^{-3}	7.0239×10^{-4}	2.2661×10^{-6}
LOLE(hrs)	2.2649×10^{-4}	1.6682×10^{-4}	2.7754×10^{-7}
LOLF(occ./hrs)	4.7232×10^{-4}	3.3880×10^{-4}	9.0088×10^{-7}

cording to our experiments with other combinations of N_1 and N_2, the best efficiency (without inadequate favor, CPU time is 6.27 min) can be achieved with $N_1 = 1200$, $N_2 = 400$, $n = 1$ and it seems that $N_1 = 60 \times K$ and $N_2 = \lceil N_1/3 \rceil$ qualifies as a safe and efficient setting.

Iteration parameter n contributes by overcoming rareness resulted from low load level combined with high reliability of component. That means the more reliable the component and the smaller ratio of load level to generation capacity is, the more iterations, which can effectively result in much more failures of components in a short lead time, are required to ensure high efficiency of the second-stage sampling against rareness. The CPU times and indices under different load levels and values of n are listed in Table III. In these experiments, $N_1 = 1260$, $N_2 = 420$ is set according to the proceeding conclusions, and $\sigma_{\mathrm{EENS}} \leq 0.05$ is still selected as the stop criterion for the third-stage simulation. The effectiveness of n to overcome rareness is validated by the following results: with $n = 0$ as reference, CPU time is saved by 94.49% ($n = 1$) in the scenario of peak load; in the scenario of 80% peak load, CPU time by the TSSIS method is 2131.28 seconds while the CSMCS method failed (CPU time $>$ 36 000 sec), which demonstrates a much higher efficiency improvement. In the scenario of 80% peak load, the slightest time consumption is obtained with $n = 2$, as the setting of $n = 1$ does not overcome the rareness sufficiently and $n = 3$ results in more failed components in each sampled system state, in which case many more iterations are required by AC (optimal) power flow to find a solution. Therefore, an inordinately large value of n with respect to system scale is not recommended if AC (optimal) power flow is called for analysis. Moreover, as indicated by our tests for other cases of prominent rareness where n is necessarily set large, N_1 should also be increased to avoid inordinate favor. By combing the proceeding conclusions, crude but safe estimations of the three parameters are represented as follows: $N_1 = 20n^2 \times K$ and $N_2 = 20 \times K$. It is also noted that the indices under the peak load are about 1000 time larger than that under the 80% of peak load, indicating that short-term reliability is quite sensitive to the load level.

The relationship of the three parameters discussed above are difficult to be generalized due to different execution environments associated with real-size power systems, however, through the investigations above, it can be concluded that setting of the parameters is strongly related to two aspects, that is the system scale and the rareness of concerned critical failure events. As these two aspects seldom fluctuate sharply in short-term reliability evaluation, these parameters can be regulated offline before the TSSIS method is called for online application.

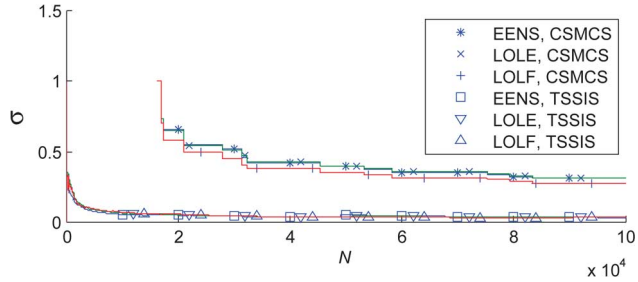


Fig. 3. Relationships between σ and the number of simulation runs under the CSMCS method and the TSSIS method respectively applied to IEEE-RTS79 with logarithmic ordinate axis. The TSSIS method is conducted with the denotation (a) for $S_{\mathrm{II}}(\Gamma)$.

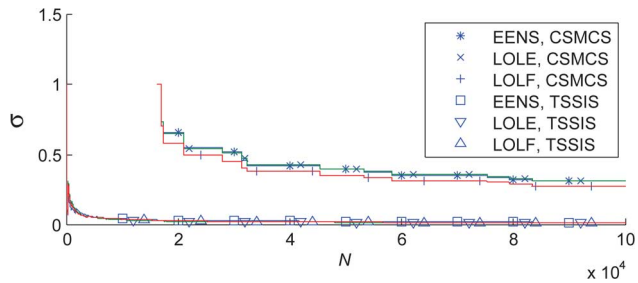


Fig. 4. Relationships between σ and the number of simulation runs under the CSMCS method and the TSSIS method respectively applied to IEEE-RTS79 with logarithmic ordinate axis. The TSSIS method is conducted with the denotation (b) for $S_{\mathrm{II}}(\Gamma)$.

B. RTS-79

In this subsection, the TSSIS method is tested on the RTS-79, the lead time is set to one hour. According to the conclusions made in above subsection, parameters are set as follows: $N_1 = 12\,780$, $N_2 = 1420$, $n = 3$. We report simulation performance by considering constant peak load and random load respectively, nevertheless, time-varying load can be easily incorporated into the TSSIS method by introducing a load curve discretized to be constant in each small time interval which can be incorporated into step 3 presented in Section II. However, the time-varying load is seldom considered in such a short interval for the short-term reliability study. If the lead time is set longer, the rareness problem of failure event may not be prominent any more, which is out of scope of our discussion. In addition, three candidate denotations of $S_{\mathrm{II}}(\Gamma)$ are selected as follows for comparison:

a) $S_{\mathrm{II}}(\Gamma)$ denotes a consequent cost of Γ concerning the energy not supplied.
b) $S_{\mathrm{II}}(\Gamma)$ denotes a consequent cost of Γ concerning the outage duration.
c) $S_{\mathrm{II}}(\Gamma)$ denotes a consequent cost of Γ concerning a number of outages.

1) Constant Load: The relations between σ and the number of simulation runs under the CSMCS method and that under the TSSIS method are plotted together in Figs. 3–5 for comparison. It is obvious that the CSMCS method is inefficient with the curve showing that there is no outage event sampled until 16 232nd run, consequently, σ_{EENS}, σ_{LOLE} and σ_{LOLF} do not exist within the initial 16 232 runs and merely drop to 0.3086, 0.3122 and 0.2773 respectively after 100 000 simulations. By comparison, σ under the TSSIS method with the three different

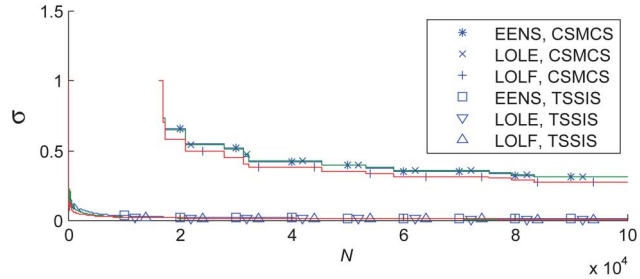


Fig. 5. Relationships between σ and the number of simulation runs under the CSMCS method and the TSSIS method respectively applied to IEEE-RTS79 with logarithmic ordinate axis. The TSSIS method is conducted with denotation (c) for $S_{\mathrm{II}}(\Gamma)$.

TABLE IV
INDICES OBTAINED BY TSSIS METHOD WITH DIFFERENT DETONATIONS FOR $S_{\mathrm{II}}(\cdot)$

	$S_{\mathrm{II}}(\cdot)$ (a)	(b)	(c)
EENS(MWh)	2.249×10^{-3} (0.0097)	$2.238 \times 10-^{-3}$ (0.0152)	2.241×10^{-3} (0.0105)
LOLE(hrs)	4.772×10^{-5} (0.0088)	4.825×10^{-5} (0.0116)	4.708×10^{-5} (0.0075)
LOLF(occ./hrs)	1.026×10^{-4} (0.0091)	1.038×10^{-4} (0.0123)	1.020×10^{-4} (0.0081)

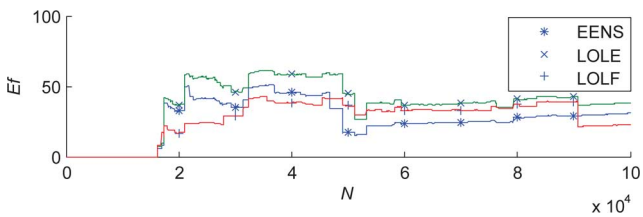


Fig. 6. The Ef associated with indices. The TSSIS method is conducted with denotation (a) for $S_{\mathrm{II}}(\Gamma)$.

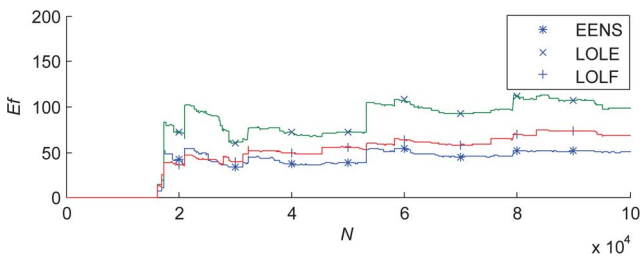


Fig. 7. The Ef associated with indices. The TSSIS method is conducted with denotation (b) for $S_{\mathrm{II}}(\Gamma)$.

detonations for $S_{\mathrm{II}}(\cdot)$ are much smaller. The numerical results of the indices listed in Table IV are similar to the published results in [10], which indicates that the TSSIS method with any of the three denotations for $S_{\mathrm{II}}(\Gamma)$ is able to approximate the same values of the indices with discrepancy of σ. We do not specify the exact computing time hereafter because our program has not been optimized.

With respect to simulation efficiency, it is easy to observe from Figs. 6–8 that different denotations for $S_{\mathrm{II}}(\cdot)$ have different effects. Ef in the case of denotation (c) shown in Fig. 8 is the highest of all, followed by that in the case of denotation (b) in Fig. 7, and Ef under denotation (a) in Fig. 6 is the lowest. It can also be noted that a significant increment of Ef comes

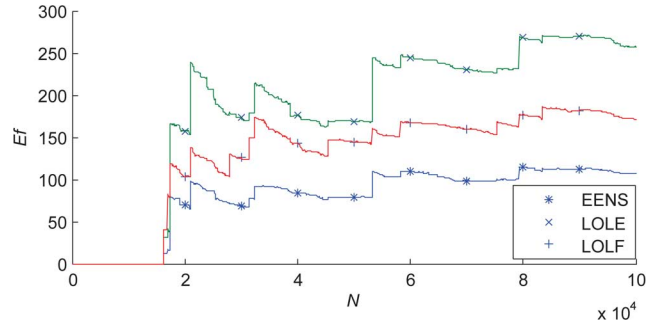


Fig. 8. The Ef associated with indices. The TSSIS method is conducted with denotation (c) for $S_{\mathrm{II}}(\Gamma)$.

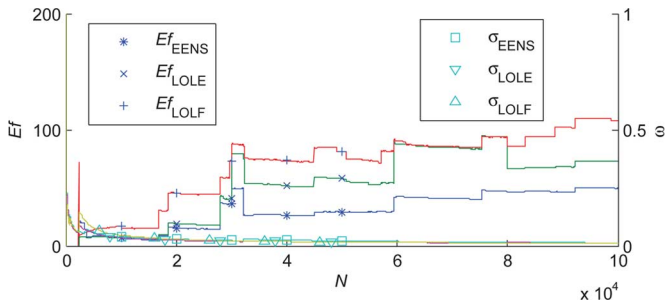


Fig. 9. Ef and σ of indices. The TSSIS method is conducted with denotation (c) for $S_{\mathrm{II}}(\Gamma)$ and load levels are independently Gaussian distributed.

TABLE V
INDICES OBTAINED BY THE TSSIS METHOD APPLIED TO RTS-79 WITH DIFFERENT DENOTATIONS OF $S_{\mathrm{II}}(\cdot)$ AND THE LOAD LEVELS ARE INDEPENDENTLY GAUSSIAN DISTRIBUTED

	$S_{\mathrm{II}}(\cdot)$ (a)	(b)	(c)
EENS(MWh)	2.307×10^{-3} (0.0121)	2.311×10^{-3} (0.0242)	2.299×10^{-3} (0.0135)
LOLE(hrs)	5.037×10^{-5} (0.0173)	4.937×10^{-5} (0.0174)	4.87×10^{-5} (0.0123)
LOLF(occ./hrs)	1.089×10^{-4} (0.0149)	1.074×10^{-4} (0.0201)	1.051×10^{-4} (0.0114)

forth at the 16 232nd simulation for all the three different denotations as there is no σ_{c} for comparison before that. As a matter of fact, σ_{EENS}, σ_{LOLE} and σ_{LOLF} under denotation (c) drop to 0.0252, 0.0185 and 0.0189 respectively at the 16 232nd simulation in Fig. 5. The results suggest that the TSSIS method with denotation (c) for $S_{\mathrm{II}}(\cdot)$ is of the highest efficiency.

2) Random Load: In this subsection, load levels for load buses are modeled as mutually independent random variables, each of which is randomly sampled at the beginning of each simulated lead time. Gaussian distribution as $L_j \sim N(\xi_j, \delta_j^2)$ is assumed for the load level of load bus j and ξ_j is assigned to annual peak value with $\delta_j = 5\%\xi_j$ for load bus j for conciseness. The samples of load below zero are discarded.

The optimal distorted ξ_j and δ_j from the viewpoint of CE are derived in the Appendix. The highest Ef is still obtained with detonation (c) for $S_{\mathrm{II}}(\cdot)$, and the Ef and σ are shown together in Fig. 9. It can be noted that Ef_{LOLF} has a significant increment of 21.81 at the 7357th run and stabilizes to approximate 100 after 60 000 runs. The numerical results of indices are listed in Table V which are proximately equal to that in Table IV as the mean load level of each load bus is assumed equal to its constant

value, respectively. The results suggest that the TSSIS method performs equally efficiently in composite short-term reliability evaluation with random load considered.

V. Conclusion

In this paper, a novel TSSIS method has been proposed to improve the efficiency of the CSMCS method applied for short-term reliability evaluation of composite power system in terms of relatively low component state transition rate with respect to a fixed short lead time.

We have reported the simulation results of EENS, LOLE and LOLF by applying the proposed method to short-term reliability evaluation of a reinforced Roy Billinton reliability test system with suggestions on the critical parameter setting of the TSSIS method. By carrying out tests on RTS-79 with different denotations for the second-stage cost function of the TSSIS method in comparison with the CSMCS method, it suggests that the TSSIS method with $S_{\mathrm{II}}(\cdot)$ denoting number of outage which is a consequent cost of system state transition path will achieve the highest efficiency gain in both constant and random load level situation. In addition, the short-term reliability indices change remarkably along with the load level. The proposed method is useful for online monitoring of system operating reliability so as to assist operators in timely decision making.

With respect to requirement of storage space in terms of application in real size system, total storage space for the TSSIS method application is proportional to the number of components as well as number of state transitions in the studied lead time. As the lead time is usually short in a short-term reliability evaluation, the overall storage space for intermediate data is trivial with respect to modern computers.

Appendix

When load is modeled as random variable, the PDF of sequential transition path with independent stochastic load considered can be constructed by multiplying (8) with PDFs of Gaussian distributions of all random load considered, which can be expressed as

$$f(\Gamma,\boldsymbol{\rho};\boldsymbol{\eta},\boldsymbol{\Xi},\boldsymbol{\Delta}) = f(\Gamma;\boldsymbol{\eta}) \prod_{j\in B} \frac{1}{\sqrt{2\pi}\delta_j} e^{-\frac{(\rho_{ij}-\xi_j)^2}{2\delta_j^2}} \tag{15}$$

where $\boldsymbol{\Xi}$ and $\boldsymbol{\Delta}$ represent respectively the set of ξ_j and δ_j. ρ_j represents a realization of load level of bus j. B is the set of load buses. Applying (10) to $f(\Gamma,\boldsymbol{\rho};\boldsymbol{\eta},\boldsymbol{\Xi},\boldsymbol{\Delta})$, it is easy to solve the optimal distorted parameters as follows:

$$\xi'^{(n+1)}_j = \frac{\sum_{i=1}^{N} \Psi_{ij}^{(n)} \rho_{ij}}{\sum_{i=1}^{N} \Psi_{ij}^{(n)}} \tag{16}$$

$$\delta'^{(n+1)}_j = \sqrt{\frac{\sum_{i=1}^{N} \Psi_{ij}^{(n)} (\rho_{ij}-\xi_j)^2}{\sum_{i=1}^{N} \Psi_{ij}^{(n)}}} \tag{17}$$

where $\Psi_{ij}^{(n)} = S(\Gamma_i,\rho_{ij})(f(\Gamma_i,\rho_{ij};\boldsymbol{\eta}_0,\boldsymbol{\Xi}_0,\boldsymbol{\Delta}_0))/(f(\Gamma_i,\rho_{ij};\boldsymbol{\eta}^{(n)},\boldsymbol{\Xi}^{(n)},\boldsymbol{\Delta}^{(n)}))$.

From (16) and (17), it can be noted that the CE-based optimal distorted parameter counting for random load is easy to be solved analytically, as the parameter has no relationship with other parameters associated with component state transitions in the same iteration step. In fact, in terms of the convenience provided by CE to deal with exponential distribution family, it is feasible to take other independent random factors, such as wind power and photovoltaic, into consideration in lead time, and the optimal distorted parameters related with these PDFs can be easily solved analytically.

References

[1] H. Mohammadnezhad-Shourkaei, M. Fotuhi-Firuzabad, and R. Billinton, "Integration of clustering analysis and reward/penalty mechanisms for regulating service reliability in distribution systems," *IET Gen., Transm., Distrib.*, vol. 5, no. 11, pp. 1192–1200, 2011.

[2] C. Singh and R. Billinton, "A frequency and duration approach to short term reliability evaluation," *IEEE Trans. Power App. Syst.*, no. PAS-6, pp. 2073–2083, 1973.

[3] A. Lisnianski, D. Elmakias, D. Laredo, and H. B. Haim, "A multi-state Markov model for a short-term reliability analysis of a power generating unit," *Reliab. Eng. Syst. Safety*, vol. 98, no. 1, pp. 1–6, 2012.

[4] P. Jirutitijaroen and C. Singh, "Comparison of simulation methods for power system reliability indexes and their distributions," *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 486–493, May 2008.

[5] A. M. Leite da Silva, R. A. G. Fernandez, and C. Singh, "Generating capacity reliability evaluation based on Monte Carlo simulation and cross-entropy methods," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 129–137, Feb. 2010.

[6] R. A. Gonzalez-Fernandez and A. M. Leite da Silva, "Reliability assessment of time-dependent systems via sequential cross-entropy Monte Carlo simulation," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2381–2389, Nov. 2011.

[7] R. Billinton and R. N. Allan, *Reliability Evaluation of Power Systems*. New York, NY, USA: Plenum, 1984.

[8] Y. Liu and C. Singh, "An analytical methodology for operational reliability evaluation of composite power system," in *Proc. 17th Power Systems Computation Conf.*, Stockholm, Sweden, 2011.

[9] X. Zou, L. Cheng, and Y. Sun, "Evaluation of cascading failure in power system based on the operational reliability theory," in *Proc. IEEE 11th Int. Conf. Probabilistic Methods Applied to Power Systems*, 2010, pp. 184–189.

[10] R. Sun, C. Singh, L. Cheng, and Y. Sun, "Short-term reliability evaluation using control variable based dagger sampling method," *Elect. Power Syst. Res.*, vol. 80, no. 6, pp. 682–689, 2010.

[11] H. Liu *et al.*, "Online short-term reliability evaluation using a fast sorting technique," *IET Gen., Transm., Distrib.*, vol. 2, no. 1, pp. 139–148, 2008.

[12] L. Cheng, X. Ye, J. He, and Y. Sun, "Sequential short-term reliability evaluation considering repair time distribution," in *Proc. 2010 IEEE 11th Int. Conf. Probabilistic Methods Applied to Power Systems*, Jun. 14–17, 2010, pp. 178–183.

[13] J. R. Ubeda and R. N. Allan, "Sequential simulation applied to composite system reliability evaluation," *Proc. Inst. Elect. Eng., Gen., Transm., Distrib. C*, vol. 139, no. 2, pp. 81–86, 1992.

[14] A. M. Leite da Silva, L. A. Da Fonseca Manso, J. C. De Oliveira Mello, and R. Billinton, "Pseudo-chronological simulation for composite reliability analysis with time varying loads," *IEEE Trans. Power Syst.*, vol. 15, no. 1, pp. 73–80, Feb. 2000.

[15] H. F. Ge and S. Asgarpoor, "Parallel Monte Carlo simulation for reliability and cost evaluation of equipment and systems," *Elect. Power Syst. Res.*, vol. 81, no. 2, pp. 347–356, Feb. 2011.

[16] R. Y. Rubinstein and D. P. Kroese, *The Cross-Entropy Method. A Unified Approach to Combinatorial Optimization, Monte-Carlo Simulation, and Machine Learning*. New York, NY, USA: Springer, 2004.

[17] R. Y. Rubinstein and D. P. Kroese, *Simulation and the Monte Carlo Methods*, 2nd ed. New York, NY, USA: Wiley, 2007.

[18] W. Wangdee and R. Billinton, "Bulk electric system well-being analysis using sequential Monte Carlo simulation," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 188–193, Feb. 2006.

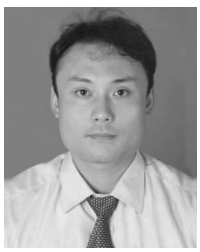
[19] P. M. Subcommittee, "IEEE reliability test system," *IEEE Trans. Power App. Syst.*, vol. PAS-98, no. 6, pp. 2047–2054, 1979.

[20] R. Billinton and W. Li, "A system state transition sampling method for composite system reliability evaluation," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 761–770, Aug. 1993.

[21] G. Rubino and B. Tuffin, *Rare Event Simulation Using Monte Carlo Methods*. Rennes, France: Wiley, 2009, INRIA.

[22] M. V. F. Pereira and N. J. Balu, "Composite generation/transmission reliability evaluation," *Proc. IEEE*, vol. 80, no. 4, pp. 470–491, 1992.

[23] M. Pupashenko and R. Korn, "Minimizing Variance and Cross-Entropy Importance Sampling Methods for Rare Event Simulation," Univ. Kaiserslautern. Kaiserslautern, Germany, 2011.
[24] R. Y. Rubinstein, *Simulation and Monte Carlo Method*. New York, NY, USA: Wiley, 1981.
[25] R. Billinton *et al.*, "A reliability test system for educational purposes-basic data," *IEEE Trans. Power Syst.*, vol. 4, no. 3, pp. 1238–1244, Aug. 1989.
[26] B. Kaynar and A. Ridder, "The cross-entropy method with patching for rare-event simulation of large Markov chains," *Eur. J. Oper. Res.*, vol. 207, no. 3, pp. 1380–1397, 2010.



Yue Wang was born in China in 1982. He received the B.S. degree in automation from Wuhan University of Science and Technology, Wuhan, China, in 2005 and the M.S. degree in electrical and electronic engineering from Huazhong University of Science and Technology (HUST), Wuhan, China, in 2007. He is currently pursuing the Ph.D. degree in electrical engineering in the College of Electrical Engineering in Zhejiang University (ZJU), Hangzhou, China.

His research interests include the power system risk assessment and power system operation security and reliability.

Chuangxin Guo (M'09) was born in China in 1969. He received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from Huazhong University of Science and Technology, Wuhan, China, in 1992, 1994, and 1997, respectively.

From 1997 to 2003, he worked as the Director of Beijing Dongfang Electronics Research Institute and the Deputy Chief Engineer of Dongfang Electronics Co., Ltd. During 2003 and 2005, he worked as a post-doctoral in electrical engineering in Zhejiang University (ZJU), Hangzhou, China. From 2005 to 2006, he was an Associate Professor in the College of Electrical Engineering (CEE), ZJU. Since September 2006, he has been a Professor in CEE, ZJU. He has authored and coauthored more than 100 technical publications, including 85 papers and one book. His research interests include smart grid, distributed energy resources attaching to power grid, intelligent information processing technology and its application in power system.

Dr. Guo is a Committee Member of CIGRE China.

Q. H. Wu (M'91–SM'97–F'11) received the M.Sc.(Eng.) degree in electrical engineering from Huazhong University of Science and Technology, Wuhan, China, in 1981 and the Ph.D. degree in electrical engineering from The Queen's University of Belfast (QUB), Belfast, U.K., in 1987.

From 1981 to 1984, he was appointed Lecturer in electrical engineering in Huazhong University of Science and Technology. He worked as a Research Fellow and subsequently a Senior Research Fellow in QUB from 1987 to 1991. He joined the Department of Mathematical Sciences, Loughborough University, Loughborough, U.K., in 1991, as a Lecturer; subsequently he was appointed Senior Lecturer 1995. In September 1995, he joined The University of Liverpool, Liverpool, U.K., to take up his appointment to the Chair of Electrical Engineering in the Department of Electrical Engineering and Electronics. Since then, he has been the Head of Intelligence Engineering and Automation Research Group working in the areas of systems control, computational intelligence and electric power and energy. He has authored and coauthored more than 360 technical publications, including 185 journal papers, 20 book chapters and 3 research monographs entitled "IP Network-based Multi-agent Systems for Industrial Automation—Information management, condition monitoring and control of power systems", "Protective Relaying of Power Systems Using Mathematical Morphology" and "Condition Monitoring and Assessment of Power Transformers using Computational Intelligence" (New York, NY, USA: Springer). His research interests include nonlinear adaptive control, mathematical morphology, evolutionary computation, machine learning and power system control and operation.

Prof. Wu is a Fellow of IET and a Chartered Engineer and Fellow of InstMC.