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Adjusted LOLE and EENS Indices for the Consideration of Load Excess Transfer in Power Systems Adequacy Studies

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***Abstract*—**When evaluating the capacity of a generation park to cover the load in transmission systems, traditional Loss of Load Expectation (LOLE) and Expected Energy not Served (EENS) indices can be used. If those indices allow computing the annual duration and severity of load non covering situations, they do not take into account the fact that the load excess is generally shifted from one penury state (hour or quarter of an hour) to the following one. In this paper, a sequential Monte Carlo framework is introduced in order to compute adjusted LOLE and EENS indices. Practically, those adapted indices permit to consider the effect of load excess transfer on the global adequacy of a generation park, providing thus a more accurate evaluation of this quantity.

***Keywords*—**Expected Energy not Served, Loss of Load Expectation, Monte Carlo simulation, reliability, wind generation.

I. Introduction

FOLLOWING the increase of wind energy in the electricity grid, new challenges have emerged. Indeed, initially built for traditional power units, the grid is not yet fully adapted to the foreseen levels of this intermittent energy resource. The previous observation has consequently motivated lots of researchers to develop methods which were able to evaluate the impact of wind power on the planning and the operation of the electrical system [1]-[3].

Practically, thanks to attractive financial policies, conventional electrical generation based on the use of fossil fuels seems to be replaced by highly fluctuating generation mainly based on the kinetic energy contained into the wind. This progressive introduction of uncertainties in the electrical systems combined with the actual issues around nuclear energy as well as with a lack of investment in the electrical infrastructure lead to a degradation of the capacity of national power systems to cover permanently their own load. In order to maintain acceptable power capacity and consequently to limit the inherent risk of black-out, reliability indices like LOLE (annual duration of load non covering situations) and EENS (mean annual energy not served) [4] need to be computed and maintained below given thresholds. If those indices give an interesting evaluation of the ability of a generation park to cover its load, it does not take into account the fact that the load excess is generally transferred from the actual penury system state (hour or quarter of an hour) to the following one with, as a consequence, an increase of the load level during this state to come. In order to be able to evaluate this effect on the adequacy of the electrical system, adjusted LOLE and EENS are introduced in this paper. In that way, a sequential Monte Carlo simulation tool is implemented and allows shifting the load excess from a problematic state to the following one.

This paper is organized as follows. In a first section, the sequential Monte Carlo framework is introduced. Then, adjusted LOLE and EENS indices are defined and implemented in the Monte Carlo tool. In a third part, the developed tool is applied to an academic test case and the differences between adjusted and non-adjusted indices are evaluated. Finally, a conclusion pointing out the interest of the adjusted indices is proposed.

II. The Sequential Monte Carlo Simulation

Monte Carlo simulations can be used to estimate reliability indices by simulating the actual process and random behaviour of the considered electrical system. In theory, those simulations can include system effects which may not be possible without excessive approximation in a direct analytical approach and can generate a wide range of indices within a single study. In fact, there are two basic techniques used when Monte Carlo methods are applied to power system reliability evaluation, these methods being known as the sequential and non-sequential techniques [5]-[8].

In the present study, a sequential Monte Carlo algorithm has been implemented under Matlab® to evaluate the reliability indices of interest. Note that the scope of the study is limited here to the hierarchical level HL-I (aggregated generation and consumption under infinite node hypothesis) and only the capacity of the electrical system to cover the load is evaluated.

A. Conventional Generation and Load Models

This Monte Carlo simulation could theoretically incorporate any number of system parameters and states but it has been here assumed that a generation unit was only able to lie in one of the following two states: ***fully available*** and ***unavailable***. The times to failure and times to repair for a yearly sequence are obtained by sampling the appropriate probability distributions. In this procedure, the state residence times are assumed to be exponentially distributed [6], [7]. Concretely, a random variable T characterizing the time between events

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(failure or repair) has thus the following probability density function:

$$f_T(t)=\lambda\cdot e^{-\lambda t} \tag{1}$$

where λ is the mean value of the distribution and represents the number of events occurring during the considered period of time. Using the inverse transform method [9], the random variable T is obtained by:

$$T = \frac{-\ln(1-u)}{\lambda} \tag{2}$$

where u is a uniformly distributed random number over the interval [0 1].

Practically, both operating and repair times of the considered conventional 2-state model for the generation units are thus exponentially distributed. MTTF and MTTR are respectively the mean times to failure and to repair. Sampling values of the times to failure (TTF) and to repair (TTR) are finally computed (2) as [6]:

$$TTF = -MTTF \cdot \ln(1-u) \tag{3}$$

$$TTR = -MTTR \cdot \ln(1-u') \tag{4}$$

with u and u' two independent uniformly distributed random numbers over the interval [0 1].

From the load point of view, an annual peak load is modulated by use of weekly, daily and hourly modulation rates provided in reference [10].

B. Wind Generation Model

In this paper, wind speed distributions are classically approached by a Weibull law [3], [11]:

$$f(W,A,B)=\frac{B}{A^B}W^{B-1}\cdot e^{-\left(\frac{W}{A}\right)^B} \tag{5}$$

$$F(W,A,B)=1-e^{-\left(\frac{W}{A}\right)^B} \tag{6}$$

with A the scale parameter, B the shape parameter, W the wind speed, f(W,A,B) the density of probability and F(W,A,B) the Cumulative Distribution Function. The parameters of each considered Weibull distribution are the ones introduced in reference [5].

Practically, the implemented wind speed sampling is based on the classical 'Inversion of Cumulative Distribution Function' method which can be summarized as follows [5]:

Step1. Sampling of an uniformly distributed number 'v' on the interval [0, 1];

Step2. Application of that sampled number to the inversed Weibull Cumulative Distribution Function $F^{-1}(W,A,B)$ in order to determine the associated wind speed 'W':

Finally, once the wind speed has been sampled, it must be converted into generated power. In that way, the following power curve is implemented [7]:

$$\begin{cases} P = 0, W < v_{ci} \\ P = c + d\cdot W^2, v_{ci} < W < v_r \\ P = P_r, v_r < W < v_{co} \\ P = 0, W > v_{co} \end{cases} \tag{7}$$

where, v_{ci}, v_r, v_{co} are respectively the cut-in, rated and cut-out wind speeds. P_r is the nominal power of the wind generator. Parameters c and d are defined as [3]:

$$c = \frac{P_r\cdot v_{ci}^{\ 2}}{\left(v_{ci}^2 - v_r^2\right)} \tag{8}$$

$$d = \frac{P_r}{\left(v_r^2 - v_{ci}^2\right)} \tag{9}$$

C. The Implemented Algorithm

For each simulated hour *i*, the state of the studied system is firstly generated. To do so, the state of each classical generation unit is changed if the simulated hour matches the associated TTF (if this unit was operating during the previously simulated state) or TTF+TTR (if the unit was down during the previously simulated state). If the state of a classical unit has been changed then a new value of TTF (if the unit has moved from down to operating state) or TTR (if the unit has moved from operating to down state) is sampled for the considered unit by use of (3) or (4). Wind generation during the simulated hour is defined by an adequate sampling on the wind speed distribution linked to each wind park, the conversion into power being made via the associated power curve. The load during the simulated hour is obtained by checking the associated modulation rates in the predefined annual profile.

After the generation step, each system state is then analyzed. Indeed, the available generation (wind + conventional generation) is compared to the load. If the load exceeds the available generation then the number of problematic states n_p is incremented. Simultaneously, for each problematic state *j*, the lack of energy E_{lj} is also evaluated by making the difference between the actual load and the available generation (energy being equal to power in this paper as hourly states are considered).

At the end of the simulation (*i* = *NS*, *NS* being the total number of states to be simulated), both reliability indices of interest are evaluated as:

$$LOLE = \frac{n_p}{NS} * 8760 \tag{10}$$

$$EENS = \frac{\sum_{j=1}^{n_p} E_{lj}}{NS} * 8760 \tag{11}$$

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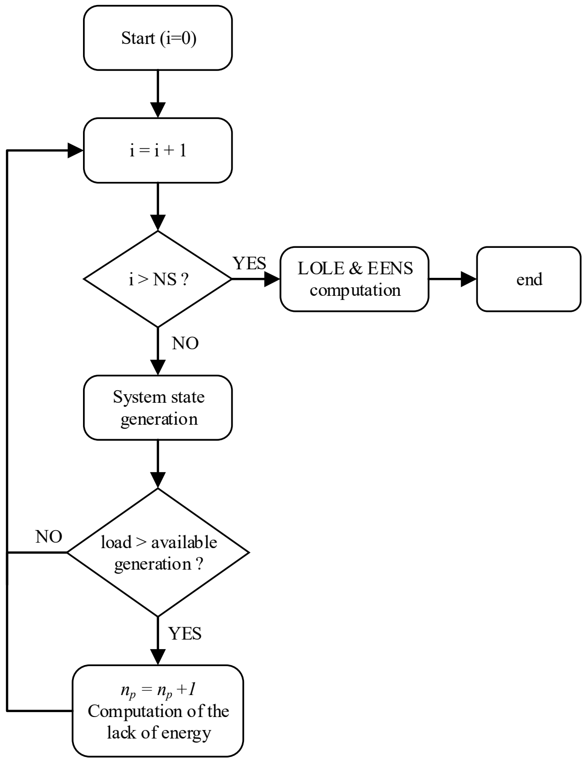

Fig. 1 Flowchart of the implemented sequential Monte Carlo simulation with computation of traditional LOLE and EENS indices

III. Adjusted LOLE and EENS Indices

As already mentioned in the introductive part of the paper, the load excess during a problematic state (lack of generation) is generally shifted towards the following one, increasing thus the consumption level of this new state. In order to compute the influence of the load transfer on the ability of the system to cover the load, the algorithm of Section II *C* needs to be slightly completed. Indeed, for each problematic state *j*, after having evaluated the lack of energy E_{lj}, this value is then added to the initial load of state $j+1$ and the resulting load is compared to the available generation of $j+1$. If a situation of load excess is also detected for state $j+1$, then the new computed lack of energy (difference between the resulting load and the available generation) is again shifted towards state $j+2$. This process of load transfer is repeated until a 'safe' state is recorded. Using this adapted framework and (10) and (11), adjusted LOLE and EENS indices that take into account load excess transfer can be computed. Those indices permit to better evaluate the adequacy of a given generation park as they integrate the practical load transfer observed after situations of generation shortage.

IV. Case Study and Simulation Results

The tested grid is based on the one depicted in [7] and [10]. Practically, the peak load is fixed to 560 kW and 15 conventional generation units are considered (10 units of 32 kW and 5 units of 60 kW). Their MTTF and MTTR are identical and respectively imposed to 2940 h/year and 50 h/year. Two wind generators (20 kW each) are added to the system and, as already mentioned in Section II *B*, are respectively based on the Weibull parameters provided in [5]. The same power curve is applied for both wind parks with v_{ci} = 3 m/s, v_r = 12 m/s and v_{co} = 25 m/s.

Two extreme correlation scenarios are implemented. The first one considers an entire correlation between the simulated wind speeds (the same random number is applied for both wind parks during step 1, Section II.*B*) and the second one is based on an entire independence between those wind speeds (different random numbers are applied for both wind parks during step 1; Section II *B*).

Practically, the number of simulated years NS of the Monte Carlo process is decided by comparing the coefficient of variation β of each index to a fixed tolerance threshold (β < 1% when computed over the last 500 years of simulation) [6]:

$$\beta_{LOLE} = \frac{\sqrt{V(LOLE)}}{E(LOLE)} \tag{12}$$

$$\beta_{EENS} = \frac{\sqrt{V(EENS)}}{E(EENS)} \tag{13}$$

where, V and E are respectively the variance and the mean value of the estimated index.

In fact, in the Monte Carlo process, a new value of both indices is calculated at the end of each simulated year. This value is based on the number of system states simulated until the ended year. The coefficient of variation β begins to be yearly computed after that 500 years have been analysed and the simulation is stopped when the convergence threshold is reached. In the present case, the convergence is obtained for NS = 4000 years (Fig. 2).

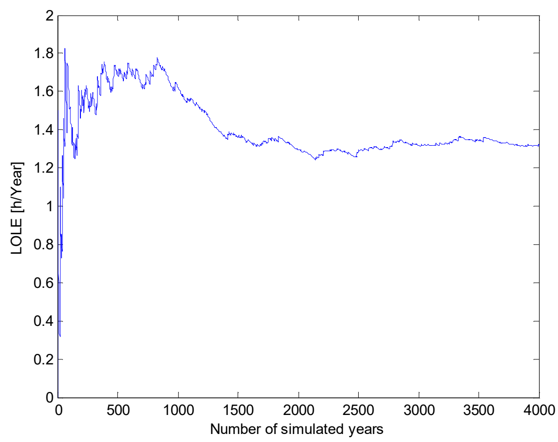

Fig. 2 Illustration of the convergence of the Monte Carlo process for NS = 4000 (evolution of the adjusted LOLE index in the entirely correlated scenario)

Table I gives LOLE, adjusted LOLE, EENS and adjusted EENS indices for both investigated scenarios. By analysing the values of those indices, it can be observed that, whatever the considered level of correlation between wind parks, taking into account the load excess transfer from one critical penury state to the following one leads to a significant degradation of the traditional LOLE and EENS indices (variation of more than 400 % of the recorded EENS indices). This observation demonstrates that computing LOLE and EENS indices without considering this practical load shifting leads to an optimistic evaluation of the adequacy of the studied generation park and could involve insufficient investment decisions when upgrading this park or interconnections with neighbouring countries. Indeed, the severity of the lack of load during penury situations is clearly underestimated by use of the traditional LOLE and EENS indices.

TABLE I
TRADITIONAL AND ADJUSTED INDICES FOR BOTH SIMULATED SCENARIOS

Simulated scenario	LOLE	Adjusted LOLE	EENS (kWh/year)	Adjusted EENS (kWh/year)
100% correlated	0.9670	1.3213	15.468	88.839
100% independent	0.9663	1.2875	15.364	87.969

Finally, it can also be observed that a slight degradation of the computed indices in the “entirely correlated” scenario can be observed. The later can be explained as follows. Practically, in the “entirely correlated” case, wind generation is simultaneously reduced for both considered units and, consequently, states of lack of available generation are more severe compared to the ones recorded in the “independent case”. Indeed, in this last scenario, a smoothing of the available wind generation is observed as the power decrease of one generator is not necessarily simultaneously observed for the other one.

V. CONCLUSION

In this paper, a sequential framework has been introduced in order to evaluate the adequacy of a given generation park. In that way, the importance of the load excess transfer from one penury state to the following one has been pointed out by the computation of adjusted LOLE and EENS indices. The obtained results have indeed shown that forgetting to consider this load shifting could lead to an optimistic evaluation of the adequacy of the studied electrical system and thus conduct to insufficient investment decisions when reinforcing the electrical system.

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