Abstract—The Itaipu Dam is a well-known hydroelectric plant located at the Paraná River, in the border between Brazil and Paraguay. With an installed capacity of 14GW, Itaipu is currently the world’s largest electric energy generation plant and the second largest in terms of installed capacity, reaching in 2012 a total generation of 98.3TWh. This work proposes a probabilistic methodology based on sequential Monte Carlo simulation (MCS) to assess the generating capacity reliability of Itaipu. The main objective is to estimate reliability indices which can quantify the risks of not having sufficient available generation capacity to meet contractual and/or system demands. All deterministic and stochastic data regarding the Itaipu generating units are directly obtained from their operating history data base. Furthermore, many chronological aspects, such as scheduled maintenance and capacity fluctuation, can be easily included in the simulation model. Finally, by taking advantage of the sequential MCS framework, the proposed method can represent both Markovian and non-Markovian state transitions, obtain monthly indices, and also estimate the annualized reliability indices probability distributions. Case studies are presented and discussed in details.

Keywords—generating capacity reliability; sequential Monte Carlo simulation; renewable energy sources; Itaipu Binacional; hydroelectric plants; risk analysis

I. INTRODUCTION

For decades, most electric power systems have been planned and operated using a set of deterministic rules, such as the N-1 security criterion [1]. Methodologies based on deterministic criteria have prevailed in the electric power sector mainly due to their simplicity of application, and because they usually provide robust solutions, both for expansion planning and operating purposes.

Deterministic methodologies, however, usually lead to a non-optimal use of the available resources and to an excessive amount of generation and transmission reinforcements [2]. These aspects have a significant impact on the operating and planning costs. Thus, the constant growth in the size of the systems, the large number of uncertainties involved, and the availability of better computational resources have promoted the development of probabilistic-based methodologies, which can efficiently deal with these new trends and provide solutions that are more compatible with the current needs of power system planners and operators.

Methodologies based on probability concepts can be extremely useful to assess the performance of power systems [3]-[4]. Regarding reliability evaluation problems, Monte Carlo Simulation (MCS)-based tools [3]-[6] have proven to be extremely useful and provide a wide-ranging reliability assessment, particularly for large and complex power systems. In addition, there has been an increasing interest in renewable energy sources such as solar and wind power generation [7]. The design of a power system with high penetration of renewable energy is more complex due to the huge number of random variables involved and the fluctuating capacity levels of these sources. Renewable power generation and detailed chronological load models are both considered time-dependent, because of their strong correlation with time and weather-related variables. Therefore, new computational models and tools need to be developed in order to efficiently deal with these new trends [8]-[9].

The Itaipu Dam is a well-known hydroelectric plant located at the Paraná River, in the border between Brazil and Paraguay [10]. With a nominal installed capacity of 14GW (20 generating units of 700MW: 10 operating in 50Hz and 10 in 60Hz), Itaipu is currently the largest electric energy generation plant in the world and the second largest in terms of installed capacity, reaching in the year 2012 a total generation of 98.3TWh. The Itaipu Dam is currently responsible for approximately 17.4% and 74.1% of the electric energy demands of Brazil and Paraguay, respectively. Therefore, because of its strategic importance for both nations, it is necessary to develop new methodologies which can adequately assess the risks associated with the market supply.

This work proposes a probabilistic methodology based on sequential MCS [11]-[12] to assess the generating capacity reliability of Itaipu. The main objective is to obtain a set of reliability indices in terms of probability, power, energy, frequency, duration, and costs [13]-[14], which can quantify the risks of not having sufficient available generation capacity to meet contractual and/or system requirements, considering a
yearly basis. All deterministic and stochastic data regarding the Itaipu generating units are directly obtained from their operating history data base [15]. Furthermore, many chronological aspects such as scheduled maintenance and the fluctuation of generating capacities (due to hydrological conditions and uncertainties) [7]-[9] can be easily included in the simulation model. In order to represent the capacity fluctuation, 29 real annual hydro series are used corresponding to the 1984 – 2012 period. In addition, by taking advantage of the sequential MCS framework, the proposed method can represent both Markovian and non-Markovian state transitions, obtain monthly indices, and also estimate the annualized reliability indices probability distributions. Particularly, monthly indices can be very useful to identify periods of the year where the system is more vulnerable and, for example, a reevaluation of the maintenance schedule can be performed. Finally, case studies are reported using real maintenance and load data from the years 2011 and 2012.

II. PROPOSED METHODOLOGY

A. Sequential Monte Carlo Simulation

The sequential MCS [11]-[12] is a powerful tool which can reproduce the chronological evolution of the system by sampling stochastic sequences of system states. These sequences are simulated considering the stochastic model of each generating unit, the maintenance schedule, the renewable generation capacity series (e.g., hydro and wind series), and the chronological load model in the same time basis.

The basic sequential MCS algorithm can be summarized as follows:

**Step 1)** Consider that the simulation starts at \( t_0 = 0 \). Sample an initial system state \( X_0 \) considering the availabilities of the generating units, the chronological load model, the maintenance schedule, the renewable capacity series, etc.;

**Step 2)** Sample the duration of individual component states according to their respective stochastic models. Evaluate the residence time for the current system state \( X_i \) as \( t_{i+1} - t_i \), where \( t_i \) represents the sampled time when the next characteristic or component of the system changes its state;

**Step 3)** Evaluate the current system state \( X_i \) and classify it either as successful or failure. If \( X_i \) represents a system failure state, then important values such as its residence time, the corresponding curtailment energy, etc., are accumulated (for later reliability indices calculation);

**Step 4)** Transit from \( X_i \) to \( X_{i+1} \). The next system state \( X_{i+1} \) is determined by the component or characteristic of the system that changed its state at \( t_{i+1} \) (e.g., equipment repair or failure, load transition, etc.). Set \( t_{i+1} = t_i + 1 \);

**Step 5)** Steps 2 to 4 are repeated until a specified simulation time period, usually \( T = 1 \) year, has been reached;

**Step 6)** Evaluate the system reliability indices \( H(y_k) \) for the \( k\)-th simulated year;

**Step 7)** Steps 1 to 6 are repeated \( NY \) times until the convergence criterion is met;

**Step 8)** Estimate the system reliability indices as the expected value of \( H \) over the \( NY \) simulated years, as shown in (1):

\[
\hat{E}[H] = \frac{1}{NY} \sum_{k=1}^{NY} H(y_k)
\]

All of the usual loss of load indices [4]-[5] can be estimated by (1), depending on the definition of \( H(y_k) \). The maximum number of simulated years and the coefficient of variation \( \beta \) [5]-[6] are examples of typically used convergence criteria.

The sequential MCS can represent any chronological aspect of the system, simulate non-Markovian state transitions, and also evaluate not only the usual reliability indices, but also their respective probability distributions. On the other hand, the sequential MCS is usually more computational demanding when compared to other techniques, such as the non-sequential MCS [5]. In order to illustrate the proposed sequential simulation procedure, Fig. 1 shows one possible output for the Itaipu’s 50Hz generating system, considering the month of March 2011. The available generating capacity in the 50Hz sector (considering equipment failures, repairs, scheduled maintenance, and capacity fluctuation) is compared to the respective sector demand. A system failure event occurs when the available generating capacity is exceeded by the load demand.

B. Reliability Indices

The generating capacity reliability (GCR) indices are statistical values that quantify, in terms of probability, energy, duration, etc., the ability of the system to meet its load demand. In this work, the following GCR indices [4]-[5] are evaluated: Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), Expected Power Not Supplied (EPNS), Expected Energy Not Supplied (EENS), Loss of Load Frequency (LOLF), Loss of Load Duration (LOLD), and Loss of Load Cost (LOLC) [13]-[14].

![Fig. 1. Sequential simulation of Itaipu’s 50Hz generating system: three events are shown with generating units 07, 01, and 09.](image-url)
As stated in the previous section, all GCR indices can be evaluated using (1), depending on the definition of \( H(y_k) \). For instance, considering the LOLP index, \( H_{\text{LOLP}}(y_k) = \text{sum of the respective durations of all failure states in } y_k \). The EENS index can be evaluated using \( H_{\text{EENS}}(y_k) = \text{sum of the respective curtailed energies of all failure states in } y_k \). For the LOLF index, \( H_{\text{LOLF}}(y_k) = \text{number of transitions that occurred from a system success state to a system failure state, considering } y_k \). The other reliability indices can be evaluated as: \( \text{LOLP} = \text{LOLE}/T \), \( \text{EPNS} = \text{EENS}/T \), \( \text{LOLD} = \text{LOLP}/\text{LOLF} \), and \( \text{LOLC} = \text{EPNS} \times \text{ESUC} \times \text{N}\text{Month} \), where \( \text{ESUC} \) represents the Electric Service Unit Cost of Itaipu, which is currently equal to 22.6 US$/kW; and \( \text{N}\text{Month} \) is the number of months in \( T \), e.g., 12. The LOLC index, as evaluated in this work, is used to estimate the reliability cost from Itaipu’s perspective, and not from the final consumers’, and can be basically understood as a penalty for not being able to meet contractual obligations.

C. System, Generation, and Load Models

As stated in the Introduction, Itaipu has a total of 20 generating units, each with a nominal capacity of 700MW. There are 10 units operating in 50Hz, which are labeled from U01 to U09A. Similarly, there are other 10 units operating in 60Hz, which are labeled from U10 to U18A. The 60Hz generation system supplies the Brazilian demand exclusively via ELETROBRAS; a conglomerate of Brazilian utilities and electric energy agents. The 50Hz generation system, however, supplies both Brazilian and Paraguayan demands. In the latter case, the supply is performed via ANDE, which is the sole Paraguayan entity responsible for generation, transmission, and distribution of electric energy. In terms of contractual obligations, Itaipu is required to have, at least, a constant generation capacity of 12600MW. However, the actual system requirements (50Hz plus 60Hz) frequently exceed this value and, therefore, a reliability analysis considering the actual demands is also necessary.

In this work, four different failure events are targeted: (i) 50Hz system: \( G_{50Hz} < (L_{\text{ANDE}} + L_{50Hz}) \); (ii) 60Hz system: \( G_{60Hz} < L_{\text{Ebras-60Hz}} \); (iii) Itaipu system: events (i) OR (ii); and (iv) Itaipu with a constant load: \( (G_{50Hz} + G_{\text{Constant}}) < 12600\text{MW} \). Events (i), (ii), and (iii) are used to estimate the generating capacity reliability indices of the 50Hz sector, the 60Hz sector, and Itaipu, respectively, considering the actual system demands. Event (iv) is used to evaluate the capability of Itaipu to meet its contractual obligations. It is important to state that all of these events can be tracked simultaneously in the same simulation process, i.e., it is not necessary to run separate programs to estimate the reliability indices of each system.

Regarding the load models, \( L_{\text{ANDE}} \), \( L_{\text{Ebras-50Hz}} \), and \( L_{\text{Ebras-60Hz}} \) are defined by a set of 8760 discrete load levels, representing, for instance, a year \( (T = 8760\text{ h}) \). It is assumed that each load level has a respective duration of one hour. The values of \( L_{\text{ANDE}} \), \( L_{\text{Ebras-50Hz}} \), and \( L_{\text{Ebras-60Hz}} \) represent the demands that were originally requested by each customer (i.e., ANDE and ELETROBRAS) in the previous working day.

Finally, in order to simulate the stochastic behavior of Itaipu’s generating units, a simple three-state model is used, which is illustrated in Fig. 2. In the proposed model, Available represents those states where the unit is capable of providing service, regardless of whether it is actually in service and regardless of the capacity level that it can provide. Planned Outage represents those states where the unavailability of the unit was scheduled in advance (mainly due to maintenance). Finally, Unplanned Outage represents an unavailability of the unit which was not scheduled in advance (mainly due to faultsfailures). This model was obtained by aggregating several other states that have similar effects. For instance, Planned Outage aggregates many other states, such as Preventive Maintenance, Corrective Maintenance, Urgent Maintenance, etc. In the proposed model, transitions between Available and Unplanned Outage are considered to be Markovian [3]. Conversely, transitions that either enter or leave Planned Outage are both considered as non-Markovian.

D. Itaipu Units Failure and Repair Rates

It was duly demonstrated in [15] that the failure (\( \lambda \)) and repair (\( \mu \)) rates of Itaipu’s generating units have a reasonable Markovian behavior. The transition rates \( \lambda \) and \( \mu \) are then evaluated in this paper using a similar procedure to the one proposed in [15]. More specifically, these rates are obtained considering a moving period of 48 months; e.g., to estimate the reliability indices for the year 2011, the transition rates are evaluated considering the generating unit’s operating history from January 2007 to December 2010. Eq. (2) and (3) are then used to calculate \( \lambda \) and \( \mu \), respectively,

\[
\lambda = \frac{N_{\text{Available} \rightarrow \text{Unplanned Outage}}}{T_{\text{Available}}} \quad (2)
\]

\[
\mu = \frac{N_{\text{Unplanned Outage} \rightarrow \text{Available}}}{T_{\text{Unplanned Outage}}} \quad (3)
\]

where the \( N_{A \rightarrow B} \) represents the number of transitions from A to B, and \( T_A \) is the time spent in state A.

Since generating units U01-U09 and U10-U18 are similar and have been in operation for many years (the last one, U18,
Scheduled Maintenance and Capacity Fluctuation

As stated in Section II-C, transitions that either enter or leave the Planned Outage state are both considered as non-Markovian. The main reason is that these events do not occur at random, nor do they follow the exponential distribution. In fact, the unavailability period for these events is usually scheduled well in advance.

In the case of Itaipu, the generating units are scheduled for maintenance considering a certain periodicity (semiannual, annual, quadrennial, etc.). Therefore, generating units are often scheduled for maintenance more than once in the same year. This maintenance policy, which is currently under revision, significantly increases the global unavailability of the generating units (i.e., planned plus unplanned). In 2012, for example, the probabilities of Available, Unplanned Outage and Planned Outage were 0.9386, 0.0170, and 0.0444, respectively.

The sequential MCS allows the representation of maintenance schedules under hourly, daily or monthly basis. For instance, consider that a given generating unit is scheduled for maintenance from $t_{M1}$ to $t_{M2}$. Basically, when a sequential MCS is carried out, this unit will be unavailable during that time interval. When the unit is not at maintenance, its stochastic behavior is represented, as usual, using Markovian assumptions. This procedure is illustrated in Fig. 3.

Another interesting feature of the proposed approach is the ability to model the fluctuation of the generating capacities, which is a typical characteristic of renewable energy sources.

TABLE II. CASE I - RELIABILITY INDICES FOR 2011

<table>
<thead>
<tr>
<th>System</th>
<th>LOLE</th>
<th>EENS</th>
<th>LOLF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[hours/year]</td>
<td>[MWh/year]</td>
<td>[occ./year]</td>
</tr>
<tr>
<td>50Hz</td>
<td>$6.5279\times10^1$ (0.60%)</td>
<td>$1.3749\times10^1$ (0.65%)</td>
<td>$1.1479\times10^1$ (0.55%)</td>
</tr>
<tr>
<td>60Hz</td>
<td>$3.2908\times10^1$ (0.85%)</td>
<td>$8.6769\times10^1$ (1.00%)</td>
<td>$4.1395\times10^0$ (0.81%)</td>
</tr>
<tr>
<td>Itaipu</td>
<td>$8.0822\times10^1$ (0.60%)</td>
<td>$2.2426\times10^1$ (0.73%)</td>
<td>$1.2629\times10^1$ (0.54%)</td>
</tr>
<tr>
<td>Contract</td>
<td>$2.8298\times10^1$ (0.54%)</td>
<td>$1.3556\times10^1$ (0.63%)</td>
<td>$4.2935\times10^0$ (0.43%)</td>
</tr>
</tbody>
</table>

In this work, the actual generating capacity when the unit is in the Available state is defined in a daily basis, according to the active hydrological series in the simulation. As stated in the Introduction, the capacity fluctuation is modeled using 29 real hydro series, which correspond to the 1984 – 2012 period. It is assumed that all series have the same probability of occurrence. The capacity for a given day is evaluated using (4), which was obtained during the generating units’ project commissioning

$$P_d = 9.6H_d - 374$$

where $P_d$ is the generation capacity in MW corresponding to the day $d$, and $H_d$ is the mean hydraulic head for that day, expressed in meters. It is important to stress that the maximum capacity outputs for the 50Hz and 60Hz units are 788MW and 766MW, respectively. Therefore, the values of $P_d$ calculated using (4) are bounded by these amounts. Also, it is worth mentioning that even if the nominal capacity of the units is 700MW, most of the time the $P_d$ values are much larger. Fig. 4 illustrates the long-term daily mean of the generation capacity, considering the 29 hydro series.

III. APPLICATION RESULTS

In this section, the proposed method will be tested using real maintenance and load data from the years 2011 and 2012. The respective values of $\lambda$ and $\mu$ are shown in Table 1. In both cases (i.e., 2011 and 2012), a $\beta_{\text{MAX}} = 1\%$ is used for all indices as the convergence criterion. All simulations are performed in a MATLAB platform using an Intel Core I5 3.3GHz processor.

A. Case I - Reliability Indices for 2011

In 2011, the peak values for $L_{\text{ANDE}}, L_{\text{Ebras-50Hz}}$ and $L_{\text{Ebras-60Hz}}$ were 1543MW, 5800MW, and 5800MW, respectively. Regarding planned outages, it was considered a total of 41 scheduled maintenances (semiannual, annual, quadrennial, etc.) distributed among the 20 generating units, totaling nearly 288 days of planned outage. Table II shows the reliability indices obtained for this year and their respective $\beta$ values. The total CPU time for this case was approximately 1.71 hours.

The LOLE and LOLF indices for the Itaipu system were respectively 80.82 h/y and 12.63 occ./y. The convergence process for the LOLE index is illustrated in Fig. 5, and its annualized probability distribution is shown in Fig. 6. Considering a fixed load of 12600MW, the LOLE and LOLF indices were 282.98 h/y and 4.29 occ./y, respectively. Notice
that the Itaipu system has a higher frequency of failure in comparison to the fixed load case, but its LOLE index is smaller. This fact indicates that the mean duration of system failures in the Itaipu system should be much smaller, when compared to the fixed load scenario. This is corroborated by the obtained values of LOLD, which were equal to 6.40 h/occ. for the Itaipu system, and 65.91 h/occ. for the fixed load case. Finally, the estimated value of LOLC for 2011 was around $4.1969 \times 10^6$ US$/y, which is not a significant amount considering Itaipu’s annual revenues (approximately, $3.29 \times 10^9$ US$ in 2012).

Fig. 7 shows the hourly demands in 2011 for both sectors. Fig. 8 and 9 illustrate the estimated monthly values for the LOLP index, considering the 50Hz and 60Hz systems, respectively. In Fig. 8, it is possible to observe that the months of January, February, and October are the most vulnerable for the 50Hz generating system. Among them, January is the most critical with a LOLP value of $2.5986 \times 10^{-2}$; which results from a combination of high demands and low capacity levels (see, Fig. 4). October was the second most critical with a LOLP value of $2.3744 \times 10^{-2}$. While there were no maintenances scheduled in the 50Hz sector for this month, the 60Hz sector had 28 days of maintenance (distributed among 4 generating units). Therefore, much of the $L_{Ebras-60Hz}$ demand was shifted to $L_{Ebras-50Hz}$, which increased the risks in the 50Hz sector. Finally, February was the third most critical with a LOLP index around $1.4737 \times 10^{-2}$. This month has basically the same issues as January, but its planned outage time for the 50Hz sector is smaller (approximately 18 days for January and 2 days for February), which contributed in lowering the risks. Regarding the 60Hz generating system (which is illustrated in Fig. 9), only February had a LOLP index above 0.01 (i.e., $2.1080 \times 10^{-2}$). This fact results from a combination of low capacity values (see, Fig. 4) and a planned outage time of approximately 25 days (distributed among two 60Hz units).

B. Case 2 - Reliability Indices for 2012

The peak values for $L_{ANDE}$, $L_{Ebras-50Hz}$, and $L_{Ebras-60Hz}$ in 2012 were respectively 1780MW, 6300MW, and 7150MW. It is worth mentioning that 2012 was the year when Itaipu achieved its current annual production record (approximately 98.3TWh) and, therefore, the mean load values are larger in comparison to 2011. For this year, 37 scheduled maintenances (semiannual, annual, quadrennial, etc.) are considered, totaling nearly 272 days of planned outage. Table III shows the estimated GCR indices for 2012 and their respective $\beta$ values. For this case, the total CPU time was $\textit{circa} 54.29$ minutes.

The LOLE and LOLF indices for the Itaipu system were 250.89 h/y and 36.54 occ./y, respectively. Fig. 10 illustrates the
convergence process for the LOLE index and, Fig. 11, its annualized probability distribution. When comparing these results with the ones previously obtained for 2011, it is possible to conclude that 2012 indices are much larger. This was expected because of the higher load levels in 2012 (the higher the demands, the higher the risks). The hourly demands for both sectors are illustrated in Fig. 12.

On the other hand, the GCR indices considering the fixed load scenario are not that different from the ones previously obtained for 2011. Notice, however, that for a constant load of 12600MW, the LOLE value in 2012 is slightly larger than its corresponding value in 2011 (288.10 h/y against 282.98 h/y), even if the total planned outage time in 2012 is smaller (272 days in 2012 against 288 days in 2011). This indicates that the maintenance schedule used for simulating 2011 is more efficient and secure than the one used for 2012. In fact, the 2012 schedule has 7 days with overlapping maintenances (i.e., more than one unit at maintenance during the same time period), all of them involving units of the same sector (50Hz or 60Hz). The 2011 schedule, however, has only 5 days with overlapping maintenances, from which only one involves units of the same sector. Therefore, while planning a maintenance schedule it is very important to consider, not only the total planned outage time, but also the periods when the maintenances will take place and the units that will be involved. Finally, regarding the LOLC index, the obtained value for 2012 was approximately 4.1507×10^6 US$/y; an amount which is slightly inferior in comparison to 2011 (4.1969×10^6 US$/y). The difference between these two LOLC values, however, is not significant and can go either way due to the EPNS indices estimation uncertainties (1.5475×10^1 MW with βEPNS = 0.63% for 2011; and 1.5305×10^1 MW with βEPNS = 0.94% for 2012).

Fig. 13 and 14 present the monthly values for the LOLP index, considering the 50Hz and 60Hz sectors, respectively. By observing Fig. 13, one can note that the 50Hz sector LOLP values are larger within the first half of the year, with the exception of October. This behavior can be explained by the
large demands in this sector during those periods of the year, as illustrated in Fig. 12. In terms of probability of failure, April was the most critical month with a LOLP value of $5.5259 \times 10^{-4}$, followed by May, October, February, and June with LOLP values of $3.6355 \times 10^{-4}$, $3.5918 \times 10^{-4}$, $3.4184 \times 10^{-4}$, and $3.1702 \times 10^{-4}$, respectively. In the 60Hz sector (Fig. 14), February was once more the most vulnerable month with a LOLP value of $2.7552 \times 10^{-4}$. Low capacities (Fig. 4) combined with a planned outage time around 25 days were the main reasons for this result. January was the second most critical month with a LOLP index of $2.4345 \times 10^{-2}$, followed by April and July, with $2.1589 \times 10^{-2}$ and $1.6677 \times 10^{-2}$, respectively.

IV. CONCLUSIONS

This paper proposed a probabilistic methodology based on sequential MCS for assessing the generating capacity reliability of Itaipu. The main objective was to obtain a set of reliability indices, which can quantify the risks associated with the market supply. In order to accomplish this task, the usual loss of load indices were estimated considering four different system configurations: (i) the 50Hz and (ii) 60Hz sectors with their respective hourly demands; (iii) the Itaipu system, which results from a combination of (i) and (ii); and the Itaipu system considering a constant load of 12600MW. All deterministic and stochastic data regarding the Itaipu generating units were directly obtained from their operating history data base. A simple three-state model (Available, Planned Outage, and Unplanned Outage) was used for simulating the stochastic behavior of the generating units. In order to represent the capacity fluctuation, 29 real annual hydro series were used corresponding to the 1984 – 2012 period.

Two case studies were presented and discussed using real maintenance and load data from the years 2011 (Case 1) and 2012 (Case 2). The LOLP values obtained for 2011 and 2012, considering a constant load of 12600MW, were respectively $3.23 \times 10^{-2}$ and $3.29 \times 10^{-2}$, representing a supply adequacy index (LOLP×100) of 96.77% for 2011 and 96.71% for 2012. Both values are above 95%, which is the goal established in Itaipu’s tactical directives for the 2013-2017 period. The GCR indices obtained for the 50Hz sector are larger than the ones obtained for the 60Hz sector. This can be explained by the higher demands in the 50Hz system during 2011 and 2012. The LOLC indices obtained for both years were very similar and do not represent significant amounts, especially when compared to Itaipu’s annual revenues. In terms of computational performance, Cases 1 and 2 spent respectively 102.34 minutes and 54.29 minutes, considering a $\beta_{\text{MAX}} = 1\%$. However, if a $\beta_{\text{MAX}} = 5\%$ is used, which is an acceptable uncertainty level for most applications, these times drop to 4.19 minutes for Case 1, and 1.91 minutes for Case 2.

By taking advantage of the sequential MCS framework, the proposed method can represent both Markovian and non-Markovian state transitions, obtain monthly indices, and also estimate the reliability indices probability distributions. In fact, monthly indices, as duly illustrated, can be very useful to identify periods of the year where the system is more vulnerable. This information could be proven valuable, both for operation and planning purposes. For instance, it can be later used as guidance for developing more efficient and secure maintenance programs (the method can be used as a tool for assessing the risks associated to a given maintenance schedule, or to compare the performances of different schedules). Finally, the proposed approach can be easily adapted to capture the stochastic behavior of other events, such as the probability distribution of the available capacities (per sector, per month, etc.), the probability distribution of the available units (for a specified period), etc.

Future works will account for the representation of transmission restrictions, as well as applications of the sequential MCS in short-term reliability assessment and probabilistic power flow, considering the Itaipu system.

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