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SEISMIC RISK ASSESSMENT OF SPATIALLY DISTRIBUTED ELECTRIC POWER SYSTEMS

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Abstract

The adequate performance of critical infrastructure such as transportation, telecommunications, healthcare, and electric power systems are essential to the resilience of communities after major earthquakes. However, assessing the seismic risk of networks is more complex than for individual structures since the performance of systems depend on several spatially distributed intensity measures and the interdependence amongst the system's components. A convenient and probabilistically consistent way of performing the assessment is by the use of a stochastically-generated earthquake catalogue. This paper computes the seismic risk of electric power systems and its methodology can be summarized in three steps: (i) sample hazard-consistent seismic scenarios; (ii) compute the overall performance of the system for each scenario; and (iii) estimate the seismic risk from the performances of all earthquake scenarios. The resulting risk is represented by the commonly used expected annual service loss of the system, but also by the complete probability distribution of accumulated deficit of electric service. The methodology is applied to the electric network in north Chile, and is used to estimate the Energy Not Supplied (ENS) and the Energy Index of Unreliability (EIU) due to seismic events. Finally, an evaluation of the effect that different sampling methods have on the expected values and uncertainty of results is presented.

Keywords: seismic risk, distributed infrastructure systems, networks, electric power systems, fragility curves

1. Introduction

Modern societies have developed their daily life based on the reliability of complex systems such as electric power, natural gas and petroleum production and distribution, telecommunications, transportation, water supply, health system, banking and finance, emergency and government services. The operation of these systems, defined as critical infrastructures, are strongly intertwined. Due to these interdependences, the disruption of any system can lead to far-reaching security and reliability effects [1]. Electric power systems are particularly important because other key sectors depend on it [2]. For example, the U.S. Presidential Policy Directive 21 identifies the Energy Sector as uniquely critical because it provides an enabling function across all critical infrastructures [3]. Chile and countries located around the Pacific Ring of Fire are especially exposed to the risk of earthquakes. Consequently, the effect of electricity blackouts produced by these seismic events requires comprehensive system risk assessment.

Assessing the seismic risk of networks is more complex than for an individual structure, which is conventionally carried out by decoupling the problem into two steps: first, compute the seismic hazard curve at the site of the structure using Probabilistic Seismic Hazard Analysis (PSHA) [4], and then estimate the vulnerability of the structure, i.e. its response to different intensity levels. This approach cannot be used to assess the seismic risk of spatially distributed systems since it does not account for the joint probability of occurrence of different intensity levels at different sites and the interdependence among the system components. Because the computation of the joint probability distribution of intensities at multiple sites is impractical, it is more convenient to estimate the seismic risk using different earthquake scenarios, and thus not computing the seismic hazard explicitly. Typically, scenarios are also needed because the assessment of network performance does not have a closed form and requires the use of numerical simulations.

To approach the named problem, different methodologies have been presented in the literature. Particularly, for the seismic hazard modelling, the required earthquake scenarios can be selected deterministically, e.g. by the use of historic events [5], multiple events obtained from seismic hazard disaggregation, or from seismic hazard maps [6]. However, deterministic methods rely on arbitrary decisions and are not probabilistically consistent. A more comprehensive solution is to construct a stochastically-generated earthquake catalogue by the use of Monte Carlo Simulations (MCS) [7-9]. A downside of using MCS is that the number of simulations needed to achieve an acceptable amount of confidence on the results might be computationally prohibitive, especially when the performance of the system does not have a closed form and must be computed with numerical simulations. Recent studies have reduced the number of required simulations by the use of variance reduction techniques, such as importance sampling [8] and *k*-means clustering [9].

As discussed in [10, 11], a comprehensive system risk analysis of electric power networks must include: hazard modelling, fragility evaluation of vulnerable components, operation of the system, and restoration of damaged components. Recently some works on seismic risk assessment of electric power networks with a comprehensive perspective [5] and with a partially comprehensive perspective, i.e. without the restoration phase [7], and with neither operation nor restoration phases [6, 12], have been developed. The operation of the electric system in these studies has been carried out by solving an Optimal Power Flow (OPF) problem, which minimizes generation costs while balancing the entire power flow at every time step, as explained by [13].

Specifically, [5] analyses the power system of the city of Los Angeles (US) where micro-components within substations are stressed by historic seismic events to assess the resilience of the system. Reference [6] uses a single return-period hazard map, which is parameterized, to obtain the electric network fragility curve and assess the vulnerability of the interdependent European gas and electric network. Reference [7] studies the power system of Sicily; where stochastically-generated seismic scenarios and an object-oriented programming is used, including a power-flow formulation for the system operation to calculate the connectivity loss of the system. Finally, [12] uses a representation of 1962 Midwestern US bulk power system contained in a circular area of 150 km diameter where earthquake epicenters are uniformly spatially generated and a retrofit prioritization decision-making model is presented.

The present study uses MCS and importance sampling to compute the seismic risk of electric power networks. The methodology, schematically shown in Fig.1, generates first a stochastic earthquake catalogue with

N_s events, which is compiled by using a recurrence model for each seismic source to sample earthquake magnitude and location. A ground motion prediction equation is then used to sample Peak Ground Accelerations (PGA) at the site of each network component and for each earthquake. Then, fragility curves are used to sample the component damage states (i.e. generation facilities and substations), and their associated downtimes are sampled from specific probability distributions that depend on their damage state. To economize processing time, only the N_d scenarios with damage are used to operate the system. With the unit commitment previously performed, the restoration of system components is carried out in every time step within the selected model time window. In a sequence of steps and together with restoration, the operation of the complete electric power network following each earthquake is modelled as a linear optimization problem (DC OPF). Finally, the Energy Not Supplied (ENS) and the Energy Index of Unreliability (EIU) are computed to characterize the seismic performance of the network. The seismic risk is estimated using the performances due to all earthquakes in the catalogue, and is expressed by the usual expected annual loss and mean annual frequency of exceedance, but also by the complete probability distribution of accumulated losses in specific time windows. The methodology is then applied to the electric power network in north Chile.

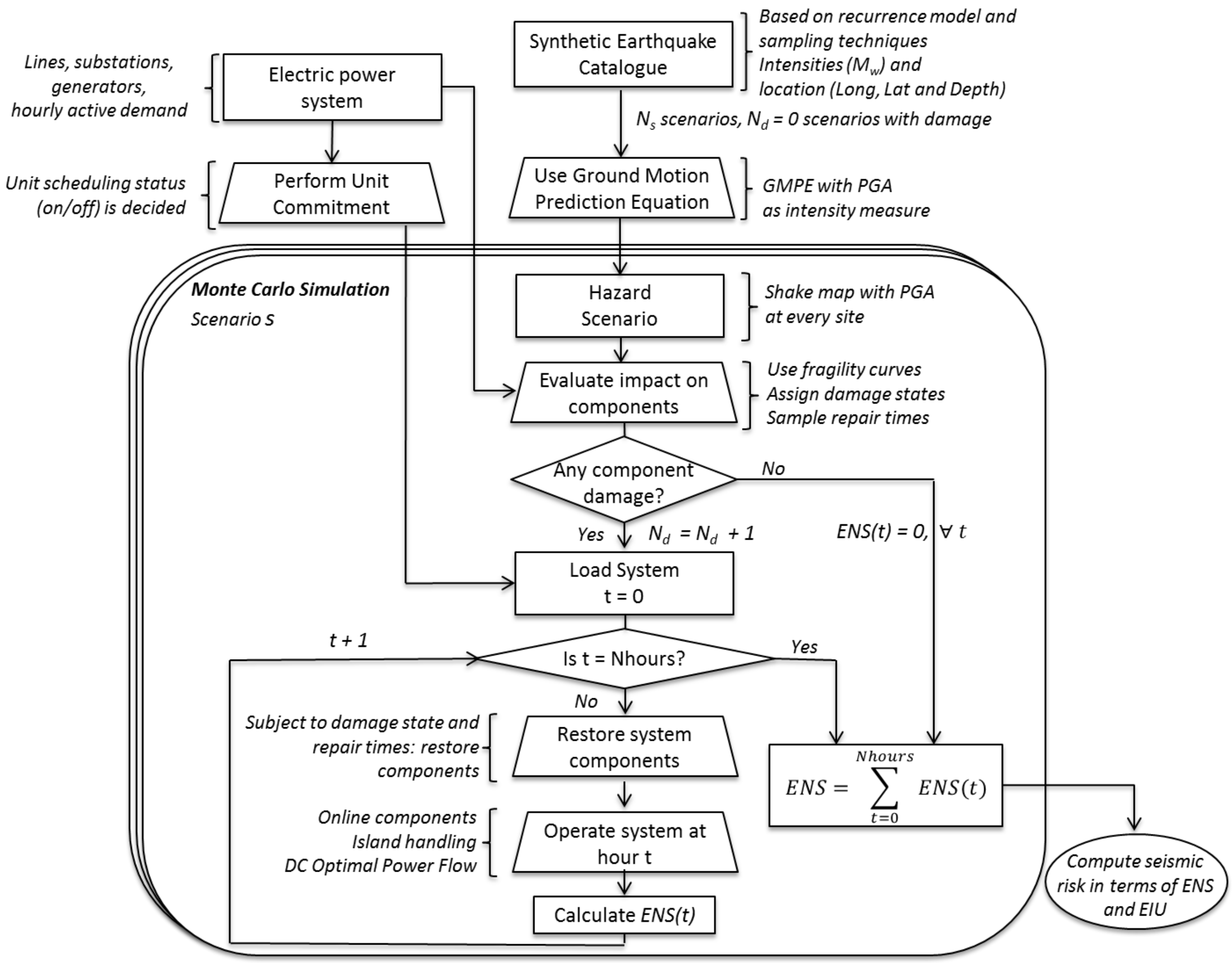

Fig. 1 – Methodology diagram.

The organization of the paper includes in Section 2 the seismic hazard modelling for spatially distributed infrastructure. In Section 3, the vulnerability and operation of electric power systems is explained and in Section 4, the risk assessment procedure is explained. A comprehensive system risk analysis of the north Chile electric network is carried out in Section 5, where normal and importance-sampling techniques are compared. Finally, Section 6 summarizes the main conclusions of the paper.

2. Seismic hazard for spatially distributed infrastructure

The first step of the methodology consists in sampling a stochastic catalogue of earthquake scenarios with their associated intensities at all locations. Earthquake magnitudes are sampled using a truncated Gutenberg-Richter recurrence model. The hypocenter location is assumed to be uniformly distributed in each seismic source. The seismic hazard model with the geometry of the seismic sources and Gutenberg-Richter parameters used in this study is presented elsewhere [14].

The intensities at all sites and for each earthquake are predicted using Eq. (1)

$$\ln(IM_{ij}) = \ln\left(\overline{IM}_{ij}\right) + \sigma_{ij}\varepsilon_{ij} + \tau_j\eta_j \tag{1}$$

where IM_{ij} is the ground motion intensity at site *i* for earthquake *j*; $\overline{IM}_{ij}$ is the average intensity predicted by a Ground Motion Prediction Equation (GMPE), which depends on earthquake magnitude, source to site distance, and other earthquake variables (e.g. focal depth and local soil conditions); σ_{ij} and τ_j are standard deviation terms representing intra-event and inter-event variability, respectively, which are also given by a GMPE; ε_{ij} is the normalized intra-event residual; and η_j is the normalized inter-event residual. Both residuals ε_{ij} and η_j are assumed as standard normal distributions. For each earthquake η_j is sampled once and ε_{ij} is sampled at each location. Inter-event residuals are also spatially correlated, which is modelled with a multivariate normal distribution with zero mean, unitary standard deviation, and a correlation structure that depends on the distances between sites [15].

The intensity measure (IM) used in this study is Peak Ground Acceleration (PGA), predicted using the GMPE proposed by Abrahamson et al [16]. This equation requires as input the average shear-wave velocity in the top 30 meters of soil (Vs30), which was obtained from seismic micro-zonation for network components inside of some cities [17]. However, the information on local soil conditions of components outside of these cities was unavailable, and hence, these velocity values were estimated using the global Vs30 map server provided by the U. S. Geological Survey [18]. The spatial correlation model proposed by Jayaram and Baker [15] is used in this study.

The previously explained procedure leads to ground motion intensities by sampling earthquake magnitudes from a truncated Gutenberg-Richter distribution (f_M). This implies sampling high magnitude earthquakes much less frequently than low magnitude earthquakes. However, high magnitude earthquake contribute more to the overall risk assessment. Therefore, a way to improve computational efficiency is to use importance sampling, where magnitudes are sampled using another distribution that increases the frequency of higher magnitude samples (g_M). This distribution has arbitrarily been selected herein as a uniform distribution. The use of a different sampling distribution must be accounted for when computing the seismic risk. This is carried out by multiplying the final results obtained by the corresponding weights expressed in Eq. (2),

$$w_i = f_M(m_i)/g_M(m_i) \tag{2}$$

where m_i is a magnitude sampled from the g_M distribution. The use of these results and weights in the overall risk assessment is explained in Section 4.

3. Vulnerability and operation of electric power systems

Electric power systems are divided in three main segments: generation, transmission and distribution. Because of their importance, the present study focuses on the first two segments, since their damage may produce a widespread blackout, whereas damage in the distribution segment may also produce local blackouts only. The system components that are identified as vulnerable to earthquakes and whose failure could possibly generate a high impact on the network's performance are power plants and substations.

Fragility curves express the probability of system components reaching different damage states, conditioned to PGA. Fragility curves assign different damage states ranging from no damage to collapse as shown in Table 1. These curves were retrieved from the technical manual of the Hazus software [19]. The Chilean electric normative [20] indicates that high voltage facilities must fulfill the ETC 1.015 standard or the IEEE 693-1997 standard at "High Performance Level". Therefore, all facilities are considered as "anchored".

Table 1 – Network components modelled as vulnerable.

Vulnerable components	Classification	Damage states
Substations	Anchored medium voltage (150 to 350 kV)	None, Minor, Moderate, Major, and Collapse
	Anchored low voltage (34.5 to 150 kV)	None, Minor, Moderate, Major, and Collapse
Power plants	Anchored large power plant (> 200 MW)	None, Minor, Moderate, Major, and Collapse
	Anchored small power plant (< 200 MW)	None, Minor, Moderate, Major, and Collapse

Each component classification and damage state has a different fragility curve. Damage states are modelled differently for each vulnerable component identified. Substations with minor, moderate, major damage and collapse disconnect 5%, 40%, 70% and 100% of adjacent components, respectively. Power plants with any damage are disconnected from the system until restored.

After assigning damage states, the restoration time of each component is defined. This depends on three main aspects: (i) the damage state, (ii) the amount of human and material resources available and (iii) the accessibility of the affected area. For simplicity reasons, in this study only the first aspect is taken into account. Restoration times are sampled from a normal distribution according to the parameters used for power plants and substations in Hazus [19].

After assigning all component damage states and repair times, the system is operated with the working components within a specified time window, say a week, and time resolution, say hourly. The operation of electric power systems is a complex topic and is performed in different ways depending on the country's, or state's, regulation, always with the objective of minimizing total costs while ensuring a reliable and inexpensive operation. Generally, the operation is delegated to an Independent System Operator (ISO) or Transmission System Operator (TSO), who performs long, medium and short-term planning to operate the system. In this work two studies are performed to operate the system: (i) unit commitment, where the scheduling of power generation units status (on/off) is decided, and (ii) DC Optimal Power Flow (DC OPF), where the dispatching of the online units is decided.

DC OPF can be modelled as a linear optimization problem where some modelling assumptions and limiting constraints are carried out. In this case, reactive powers and voltage magnitudes are omitted from the problem, and active power flows are modelled as linear functions of the node voltage angles (Θ_k - Θ_j). The decision variables of the problem are power generation of each generator unit i (p_i) and the voltage angle of each node k (Θ_k). The problem is cast as follows:

$$\min_{p_i,\Theta_k} \sum_{i=1}^{n_g} C_i\,(p_i) \tag{3}$$

$$subject\ to$$

$$(k\ \in 1 \ldots\ K\ nodes, \qquad j\ \in 1 \ldots\ J\ connected\ nodes, \qquad i\ \in\ 1 \ldots\ n_g\ generators)$$

$$g_k(p_i, \Theta_k) = p_k^{load} - \textstyle\sum_{i=1}^{n_g} A_k^i * p_i + \sum_{j=1}^{J} B_{kj} * \left(\Theta_k - \Theta_j\right) = 0, \quad \forall k \tag{4}$$

$$h_{from}(\Theta_k) = \ B_{kj} * (\Theta_k - \Theta_j) - F_{max} \le 0, \quad \forall k, j \tag{5}$$

$$h_{to}(\Theta_k) = \ -B_{kj} * (\Theta_k - \Theta_j) - F_{max} \le 0, \quad \forall k, j \tag{6}$$

$$\Theta_k^{ref,min} \le \Theta_k \le \Theta_k^{ref,max}, \quad \forall k \tag{7}$$

$$0 \le p_i \le \mathrm{p}_i^{max}, \quad \forall i \tag{8}$$

where the objective function (3) is to minimize the generation polynomial costs, assumed linear in this study, subject to: (4) real power balance constraints for each node *k*, where, as stated by Kirchhoff's laws, demand minus nodal generation plus net branch active power flow has to be zero (A_k^i is a generation connectivity matrix; where its elements are equal to 1 if generator *i* is connected to node *k* and 0 otherwise); (5,6) real power thermal constraints for each branch, where real power flow on every branch is equal to the branch susceptance, B_{kj}, multiplied by its adjacent node angles difference; (7) voltage angle constraints of each node; and (8) real power production constraints for each generator.

Finally, to incorporate the whole process, from the seismic shock to the restoration of the system, a time-dependent metric is required. In this study the Energy Not Supplied (ENS) and the Energy Index of Unreliability (EIU), presented by Allan and Billinton in [21] are used. As explained in Eq. (9), EIU represents the relation between the ENS during the time window of study and the energy demand in the complete study period E_{demand}.

$$EIU\ [\%] = \frac{ENS\ [MWh]}{E_{demand}\ [GWh]} * 100\% \tag{9}$$

4. Risk assessment of spatially distributed systems

The seismic risk of a network with *n* spatially distributed components can by assessed by computing the mean annual frequency of exceedance, λ_{PV}, of a certain performance variable (*PV*). This frequency is computed by conditioning to a ground motion intensity measure (IM) and using the total probability theorem:

$$\lambda_{PV}(pv) = \nu P(PV > pv) = \nu \int_\Omega P(PV > pv|\boldsymbol{IM} = \boldsymbol{im}) f_{\boldsymbol{IM}}(\boldsymbol{im})\ d\boldsymbol{im} \tag{10}$$

where $\boldsymbol{IM}$ is a vector of random variables representing the intensities at all locations; $f_{\boldsymbol{IM}}$ is the joint probability density function of intensities; ν is mean annual rate of significant seismic events; and $\Omega \subseteq \mathbb{R}^n$ is the domain of studied intensities. Eq. (10) assumes that the system is restored to its initial state (i.e. all components are repaired) before the next earthquake occurs. There are several reasons that make the application of this equation very difficult. First, the distribution $f_{\boldsymbol{IM}}$ is not a result that can be obtained from conventional PSHA [4], and its computation is impractical. Second, the performance of the network (*PV*) is normally obtained from numerical simulations, making it impossible to express in a closed form. Finally, the dimension of the integral is equal to the number of network components, making typical numerical quadrature rules highly inefficient. Therefore, it is more convenient to estimate the seismic risk using a set of finite stochastic earthquake scenarios generated by Monte Carlo simulations, each associated with intensities at all component locations, as explained in Section 2.

After the network performances of all simulation have been computed, the distribution of performances can be constructed by counting the number of events that surpass different threshold levels:

$$\lambda_{PV}(pv) = \nu E[\mathbf{1}(PV > pv)] \approx \nu \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(PV_i > pv) \tag{11}$$

where N is the number of considered scenarios; PV_i is the performance of the i-th scenario; and $\mathbf{1}(PV_i > pv)$ is an indicator function (i.e. its value is 1 if $PV_i > pv$ and 0 otherwise). If the scenarios are generated using importance sampling, the results must be multiplied by the weights computed during the scenario generation process to account for sampling from custom probability distributions.

$$\lambda_{PV}(pv) \approx \nu \sum_{i=1}^{N} \widetilde{w}_i \mathbf{1}(PV_i > pv) \tag{12}$$

$$\widetilde{w}_i = w_i / \sum_{j=1}^{N} w_j \tag{13}$$

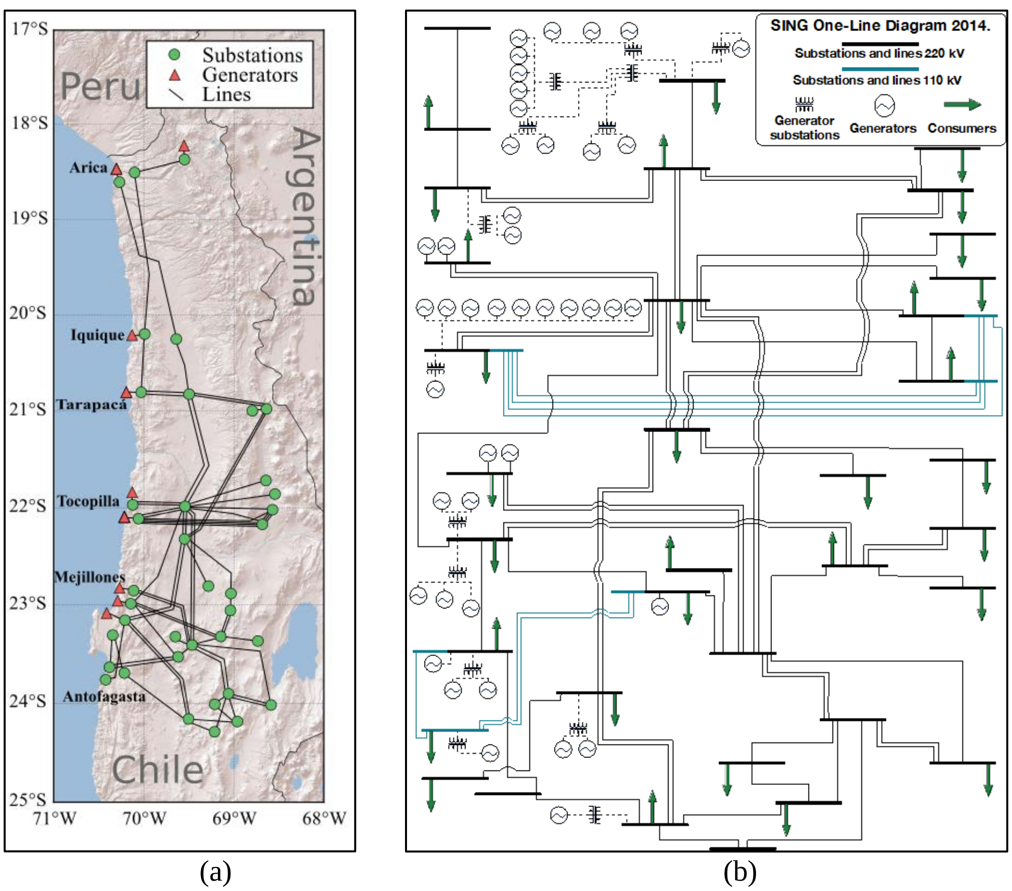

Fig. 2 – (a) Northern Chilean System geographic diagram. (b) Northern Chilean System network diagram.

5. Risk assessment of the northern Chile electrical network

The northern Chilean system (SING) serves the regions of Arica-Parinacota, Tarapacá, and Antofagasta, which cover 25% of the continental Chilean territory but only 7% of its population. In 2014 the installed generation capacity was 3744 MW; where 2100 MW was coal (56%), 1180 MW was diesel (31.5%) and 436 MW was GNL (11.5%). The peak demand of the same year was 2363 MW. The system supplies approximately 60% of the Chilean mining industry, responsible of 15% of the Chilean GDP and 49% of Chilean exports in 2011. Therefore, any interruption in the electrical supply could be economically catastrophic. Fig.2 (a) shows the geographic information of the most important components of the SING as of 2014. It is important to note that most of the generation is at the coast, while the mining consumers are located in the mountains, approximately 200 km away. Fig.2 (b) is a diagram that presents the network in detail including 36 substations, 69 lines of 220 kV and 110kV, 14 generator substations, 43 generators, and consumers (more information in [22]).

A study time window of one week with an hourly resolution was selected to perform the network simulations. Regarding the operation of the system, a simplified unit commitment was performed by running a DC-OPF for every hour of the week including 70 MW of reserves. As a result, the unit status scheduling (on/off) is determined. When a seismic scenario with damage on the components is simulated, the unit status and start-up times are considered when running the sequential DC-OPFs at each time step. Fig.3 illustrates the response of the system to four different simulated earthquakes in terms of percentage of energy demand being supplied. The figure shows that immediately after the earthquake there is a great loss of energy supply due to physical damages in components, and that the percentage of energy demand being supplied increases as the network topology changes due to offline components starting-up and damaged components being repaired. Moment magnitudes for each of the earthquake scenarios are also presented in the figure; however, the impact on the supplied energy also depends on the epicentral location, justifying that a scenario with M_w 7.4 can have a greater impact than a scenario with M_w 7.7.

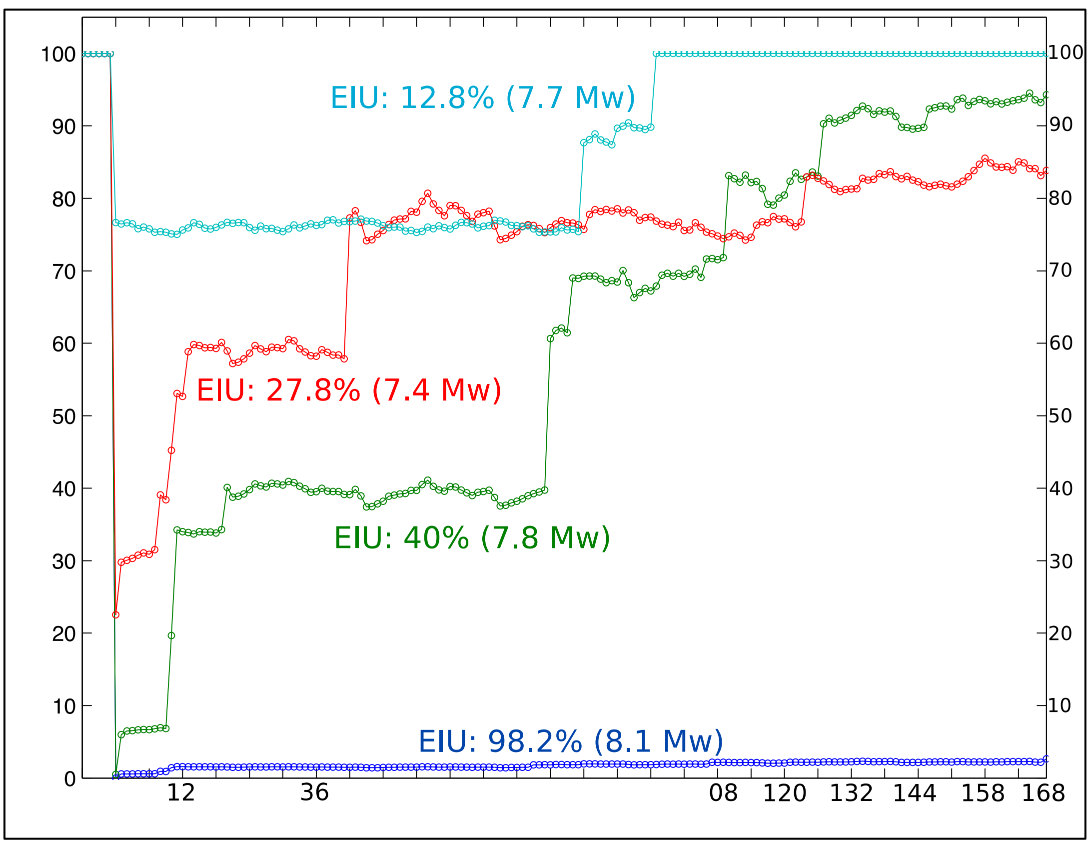

Fig. 3 – Evolution of hourly serviceability (i.e. hourly capacity to supply energy demand) for four different simulated scenarios.

As explained in the previous section Eq. (11) and (12) were used to compute the mean annual frequency of events exceeding different values of EIU from the conventional MCS and with importance sampling, respectively. The associated return periods are equal to the inverse of these frequencies ($T = 1/\lambda_{PV}$), and are shown in Fig.4 (a). The most time consuming step of the methodology is to simulate the operation of the electric power system, used to compute the unsupplied energy given the damage states and downtimes of all components. However, if a scenario does not generate any component damage, the system will operate normally and the operation step is not required. This happens less frequently when using importance sampling since the magnitude distribution used for sampling is shifted. Therefore, in order to produce a fair comparison in terms of computational time of both methods, the same amount of N_d = 26,000 earthquake scenarios that generated damage were considered in both cases. The total number of originally sampled scenarios, N_s, was approximately 55,000 and 32,000 for conventional MCS and importance sampling, respectively. Fig.4 (a) also presents a 99% confidence interval on the results, which clearly show that the importance-sampling scheme has been successful in reducing the variance of conventional MCS.

The area under the λ_{PV} curve can be used to estimate the expected energy that will not be supplied in a year, commonly known as expected annual loss (EAL) in the literature. Both sampling technics resulted in similar EAL of 1.49% (normal MCS) and 1.45% (importance sampling), which have an energy equivalent of 5.00 GWh and 4.94 GWh, respectively. This common output of seismic risk analyses represents mean losses and cannot represent their associated uncertainty. A more comprehensive probabilistic description of the losses can be achieved by computing the accumulated losses for all earthquakes that occur in specific time window [23]. Fig.4 (b) shows the cumulative distribution functions (CDFs) of these accumulated losses (i.e. non supplied energy). The previously computed EALs are equivalent to the expected value of these distributions divided by their associated time windows.

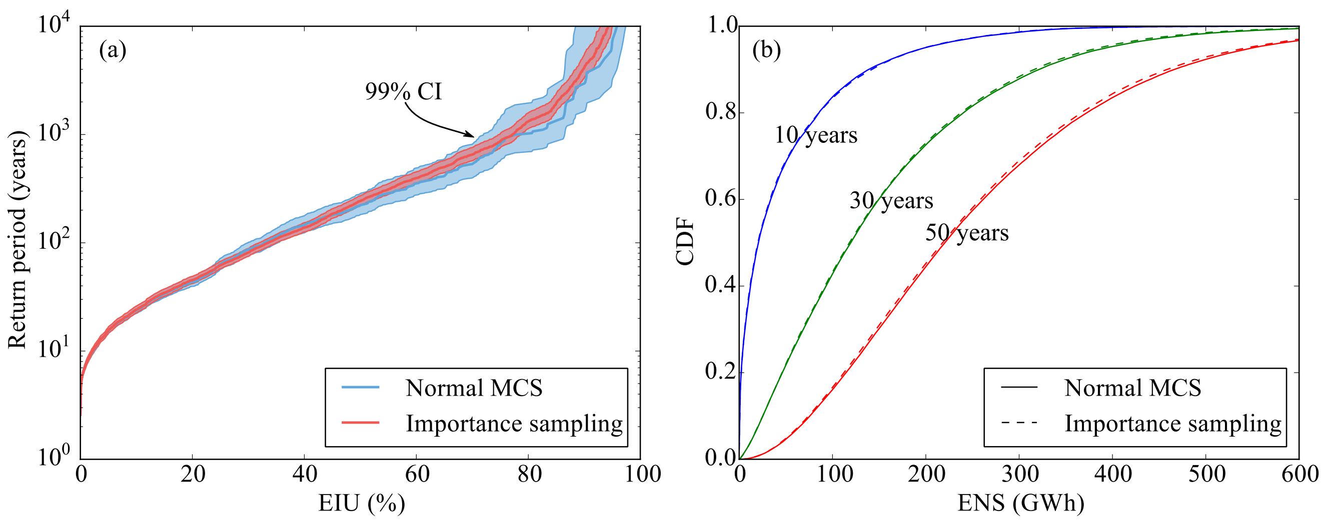

Fig. 4 – Results from the seismic risk assessment using conventional MCS and importance sampling: (a) return period of events exceeding certain values of Energy Indices of Unreliability; and (b) CDFs of accumulated unsupplied energy (ENS) for different time frames.

6. Conclusions

This work presents a seismic risk assessment methodology for spatially distributed electric power systems, and applies it to the electric network in north Chile. The evaluation uses Monte Carlo simulations to stochastically generate earthquake scenarios and compute the risk of the system using its response to all scenarios. The methodology is probabilistically consistent since it does not rely on simplifications of the seismic hazard or an arbitrary selection of earthquake scenarios used in most of the reviewed literature. However, the consistency comes with the cost of increasing the computational effort significantly since the amount of earthquake scenarios that must be used is much more than the amount that would be selected deterministically. Therefore, variance reduction techniques can be used to decrease the number of scenarios required to generate results with the same confidence level. In particular, this work used importance sampling as an alternative to generate earthquake scenarios, resulting in an improvement in the confidence intervals of the results of the MCS.

The effects of future earthquakes on the electric network were characterized by the unsupplied energy during the first week following each seismic event. The resulting risk was expressed in terms of the commonly used Expected Annual Loss, approximately 5 GWh, and the mean annual frequencies of exceedance. Results are also included for the complete accumulated distribution of losses. This last result is more meaningful for decision makers since it provides the probabilities of exceeding certain loss thresholds. Probability distributions as the ones computed in this work can be used to consider the effects of future earthquakes at the design phase of an electric network or to assess the effectiveness of possible mitigation actions that can be taken to decrease the associated seismic risk.

Possible future improvements of the risk assessment methodology would be to consider aftershocks, cascading effects that reflect the propagation of tripping components, a more complex unit commitment model, and to replace the weekly time window used to calculate the unsupplied energy following an earthquake by the time required to completely restore the service.

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