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A Monte Carlo methodology for earthquake impact analysis on the electrical grid

Brandon Johnson *, Vishvas Chalishazar, Eduardo Cotilla-Sanchez, Ted K.A. Brekken

Oregon State University, Corvallis, OR, 97330, USA

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ABSTRACT

Earthquakes present an all-encompassing threat to electrical power systems. Many grid components are highly vulnerable to direct and indirect earthquake damage. This paper presents a Monte Carlo based methodology to evaluate the seismic impact on a large & complex power system. The proposed methodology uses the concept of Performance Based Earthquake Engineering (PBEE) to quantify failure probabilities for individual assets in the power system. Individual assets are modeled using an augmented bus-branch model which leverages commonly used substation layouts to provide additional granularity. Seismic resilience is quantified using Monte Carlo simulations (MCS) to compute probability distributions for demand not served (DNS) in each studied scenario. The proposed methodology is applied to the IEEE Reliability Test System 1996 (RTS-96), which is used as a representative model of the Oregon network, and simulates the effect of a magnitude 8 earthquake. Simulated results are compared to historical data and recent benchmarking studies that examine the effect of cascading outages on the RTS-96. Results suggest that the probability of demand lost follows a comparable exponential trend to the benchmarks. Furthermore, the experiments indicate that gradual failures can result in a more robust system, as opposed to systems in which many hardened components fail simultaneously.

1. Introduction

Oregon, located in the Pacific Northwest region of the United States of America, received its statehood in the year 1859 but, until the 1980s, residents were largely unaware of the Cascadia Subduction Zone (CSZ) being an active seismic fault [1]. The state's building codes were amended and in 2011 the House Resolution 3 was passed by the Oregon legislature and Oregon Seismic Safety Policy Advisory Commission (OSSPAC) was formed. OSSPAC was tasked with developing a resilience plan for the state of Oregon [1]. Today, there are multiple initiatives carried out by multiple organizations to make the state inhabitants aware and better prepared for this threat. For the electrical grid specifically, in 1997 the Institute of Electrical and Electronics Engineers (IEEE) developed IEEE Std. 693, a recommended standard practice for seismic design of substation equipment [2]. This standard was revised in 2005, and was recently revised again in late 2018.

This recent shift to a resilience based assessment of the power system from a reliability based one has spawned a whole new field of research. The necessity of being able to model the consequences of a high impact low frequency disaster, like a magnitude 9.0 CSZ earthquake, has taken center stage in the last decade. The damage statistics of the 2011 Tohoku earthquake in Japan shows that, in the immediate aftermath of the magnitude 9.0 earthquake, 4.4 million homes were out of power. Fortunately, approximately 95% of these homes were restored with power in seven days [3]. The main earthquake on March 11, was followed by a big aftershock on April 7. This time again 4 million homes lost power but almost all of them were restored in less than four days. This shows the adaptive capability and disaster preparedness of the Japanese grid. Similar phenomenon was observed between the magnitude 9.5 Chilean earthquake of 1960, when complete electrical infrastructure of the country was capsized, and the magnitude 8.8 Maule-Chile earthquake of 2010 when the electricity supply was almost restored in 24 hours [4]. This was primarily the result of adding redundancies in the system [1]. Similar preparedness needs to be displayed by the WECC system in the aftermath of a magnitude 9.0 CSZ event. To optimally add the redundancies and preemptively retrofit the most consequential assets, critical assets need to be identified. The proposed framework intends to build the case for the same and provides a road map towards achieving this goal.

While the field of seismic resilience as applied to power systems is still being developed there are few academic papers that stand out. In reference [5], a multi-phase resilience model was used to assess the resilience of the simplified British electrical network. Reference [6] applied a sequential Monte Carlo methodology to a small electrical network to assess the resilience towards high wind speeds. So although some applications of related methodologies are seen in literature, there remains significant research opportunities in this area. This paper adopts a Monte Carlo methodology that implores the use of the Performance Based Earthquake Engineering (PBEE) [7–9] to ascertain the probability that electrical assets will fail as the result of an earthquake.

The PBEE method was first developed by researchers at the Pacific Northwest Earthquake Engineering Research (PEER) to assess the performance of buildings and bridges when exposed to earthquake-like shaking. This methodology is adapated for the power system because of its effectiveness in dividing

* Corresponding author.
E-mail address: mr.bsjohn@gmail.com (B. Johnson)

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up the seismic risk assessment problem into four parts, shown in Fig. (1). It has been identified in the post event analysis of several earthquakes that the electrical assets most at risk to failure from prolonged shaking are generators, transformers, loads, and breaker switches [3,10]. Transmission lines, although a critical asset, have proven to be very resilient to shaking [11,12], although secondary impacts such as landslides can be devastating [13]. Breaker switches are unable to be modeled in the traditional bus-branch model. To solve this issue the methodology developed by the authors in [14] is applied to convert a bus-branch model to an augmented bus-branch model. This new augmented model is a more accurate representation of the power system while maintaining a comparable accuracy to the original bus-branch model. To asses the power systems vulnerability to earthquakes a non-sequential Monte Carlo method is used. Further, a reliability assessments metric, namely the Demand Not Served (DNS), is adopted to quantify the overall impact of an earthquake.

The remainder of this paper is outlined as follows. In Section 2 the PBEE method and how to model the failure of electrical assets is explained. In Section 3 an overview of the augmentation of the traditional bus-branch model is provided. Next, in Section 4 a method to quantify the impact an earthquake has on the power system is outlined. Then in Sections 5 and 6 the simulation setup, assumptions, and results are described. Lastly, the concluding remarks that highlight the key findings of this research are presented in Section 7.

2. Performance based earthquake engineering (PBEE) method

2.1. Background and mathematical formulation

The PBEE method is a deductive technique which divides the problem of determining the risk of structural failure, when exposed to seismic shaking, into four steps. These steps are as follows:

- **Hazard Analysis**: The analysis starts by gathering information about the seismic hazard H and the probability that the hazard will occur $p[H]$. More specifically, the probability that the hazard will occur given location information about a particular asset A. This conditional probability is denoted as $p[H|A]$.
- **Structural/Response Analysis**: The second step in the PBEE process is to then determine an asset A's response R to the particular hazard H. This is primarily based on the location of the asset but device design can also play a role, e.g., how the asset is placed on the foundation. Similar to the Hazard Analysis, the probability that an asset will have response R given a hazard H is denoted as $p[R|H]$.
- **Damage Analysis**: Next, given the response R of asset A in the previous step, the probability, and extent, of the damage D is calculated. This is formally defined as $p[D|R]$. Unlike the previous steps, the extent of damage is included in this step because, depending on the response, an asset can be fully operational, fully nonoperational, or somewhere in between. This mostly dependant on device design and not location.
- **Loss Analysis**: The final step of the PBEE method is to evaluate the overall loss L of asset A given the particular damage D, i.e., $p[L|D]$. This value is final decision value which will inform an engineer about the seismic risk for an asset.

There are multiple factors that affects the earthquake energy at the equipment location. Some of these are 1) The distance of the equipment from the epicenter of the earthquake, 2) The soil type at the location, 3) The resonant frequency of the soil type and 4) The resonant frequency of the equipment-foundation combination. Depending on these factors the shaking observed by the equipment is either attenuated or intensified. It also decides whether there will be any liquefaction observed at the cite. Researchers at the Pacific Earthquake Engineering Research (PEER) use Deterministic Seismic Hazard Analysis (DSHA) method to measure/assess the PGA at any particular location [15]. In the DSHA method there are two different uncertainties involved 1) Aleatory - Arising from the randomness of the earthquake event and 2) Epistemic - Arising from the models [16], [17], [18] and [19] used to calculate the ground motion [20]. Evaluating ground motion at specific equipment locations we get the $P[R|H]$ from 1. Although for the purposes of this study, we assume three ground motion intensities for three different regions of the RTS-96 system as shown in Fig. 7.

Using the conditional probabilities listed above, the probability of response $p[R]$, probability of damage $p[D]$, and probability of loss $p[L]$ are defined using the law of total probability as:

$$p[R] = \int p[R \mid H]\; p[H]\; dH \tag{1}$$

$$p[D] = \int\int p[D \mid R]\; p[R \mid H]\; p[H]\; dR\, dH \tag{2}$$

$$p[L] = \int\int\int p[L \mid D]\; p[D \mid R]\; p[R \mid H]\; p[H]\; dD\, dR\, dH \tag{3}$$

As can be seen in (3), the seismic risk evaluation is broken up into four separate problems through the use of intermediary variables H, R, and D. Then, each variable is re-coupled through use of integration giving an overall measure of risk $p[L]$. For illustrative purposes, in Fig. (2) shows the process of evaluating an asset that is exposed to two types of hazards, has two possible responses, two damage states, and, based on those damage states, has two loss states. In matrix form the above model using the conditional probabilities $p[H|A]$, $p[R|H]$, $p[D|R]$, and $p[L|D]$ are represented as:

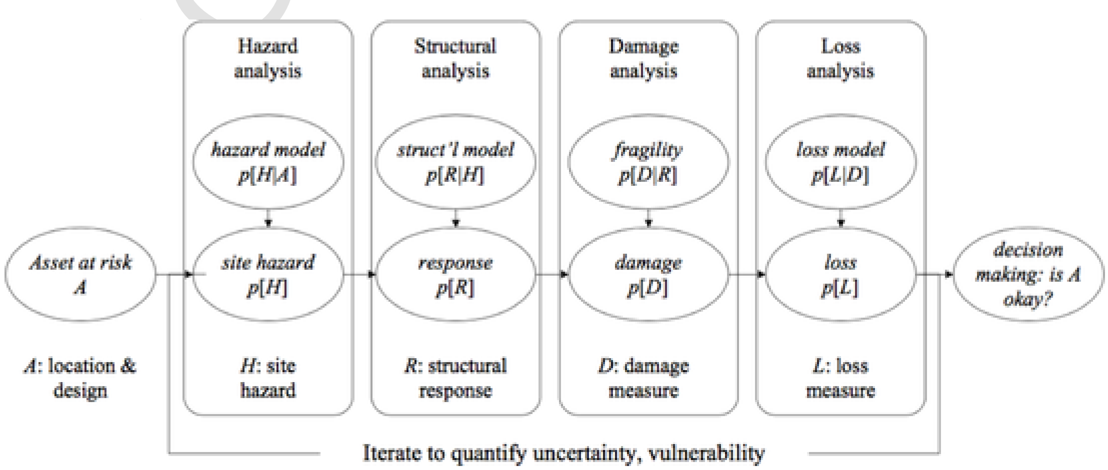

Fig. 1. Flow chart of the PBEE method[9].

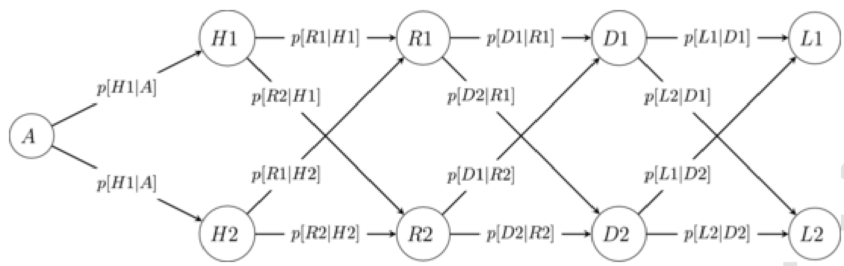

Fig. 2. Example graphical representation of the PBEE method [21].

$$
\begin{aligned}
p\,[H \mid A] &= \begin{bmatrix} p\,[H1 \mid A] & p\,[H2 \mid A] \end{bmatrix} \\
p\,[R \mid H] &= \begin{bmatrix} p\,[R1 \mid H1] & p\,[R2 \mid H1] \\ p\,[R1 \mid H2] & p\,[R2 \mid H2] \end{bmatrix} \\
p\,[D \mid R] &= \begin{bmatrix} p\,[D1 \mid R1] & p\,[D2 \mid R1] \\ p\,[D1 \mid R2] & p\,[D2 \mid R2] \end{bmatrix} \\
p\,[L \mid D] &= \begin{bmatrix} p\,[L1 \mid D1] & p\,[L2 \mid D1] \\ p\,[L1 \mid D2] & p\,[L2 \mid D2] \end{bmatrix}
\end{aligned} \tag{4}
$$

In this discrete form, the evaluation of (3) then becomes a simple matrix multiplication with the solution being as follows:

$$p\,[L] = p\,[L \mid D]\ p\,[D \mid R]\ p\,[R \mid H]\ p\,[H \mid A] \tag{5}$$

2.2. Fragility functions

A fragility function specifies the probability of occurrence of an undesirable event, such as the failure of an asset or component or transition to undesirable state, as a function of a measurable response [9]. There are many candidate function types of fragility function modeling, such as logistic functions [10], but in this research the log normal distribution function is used, as it is simple, and tends to provide a good model for natural events that follow a logarithmic pattern of occurrence or intensity, such as earthquakes.

The log-normal distribution function follows from the assumption of a standard normal random variable *Z*. The log-normally distributed random variable *X* is then defined as $X = e^{\mu+\sigma Z}$. The cumulative distribution function of *X* is then

$$F\,(x) = \frac{1}{2}\left[1 + erf\left(\frac{\ln(x) - \mu}{\sigma\sqrt{2}}\right)\right] \tag{6}$$

This function, an example of which is shown in Fig. 3, is utilized in this research as the prototypical form of the fragility function, parameterized by μ and σ.

For illustration purposes, Fig. (3) shows an example fragility function with a mean of $\mu = \log(0.5)$ and a standard deviation of $\sigma = 0.25$. Here, it can be calculated that the probability that an asset, given a PGA response of R1, will be in either damage state D1 ($p[D1|R1]$) or D2 ($p[D2|R1]$). As shown, if the system response state *R*1 is 0.6, the probability of being in either damage state *D*1 or *D*2 is 23% and 77%, respectively.

2.3. Critical electrical assets

Many historical events have given insight into which assets tend to fail more frequently when subjected to an earthquake. In the aftermath 2011 Tohoku Earthquake, the list of damaged electrical assets were categorized into generation facilities, substations, transmission facilities, and distribution facilities [3]. It was shown that the generation facilities were fairly resilient as only 30 - 55% of the total generation capacity was lost as a result of the earthquake. Damage to substations, on the other hand, were substantial. Breakers, switchgears, and isolators–common components inside generation and substation facilities–failed at a large rate which can cause a cascading effect leading to larger outages. It was shown that, although some were damaged, that transmission towers/lines and distribution poles/lines were fairly resilient. This was

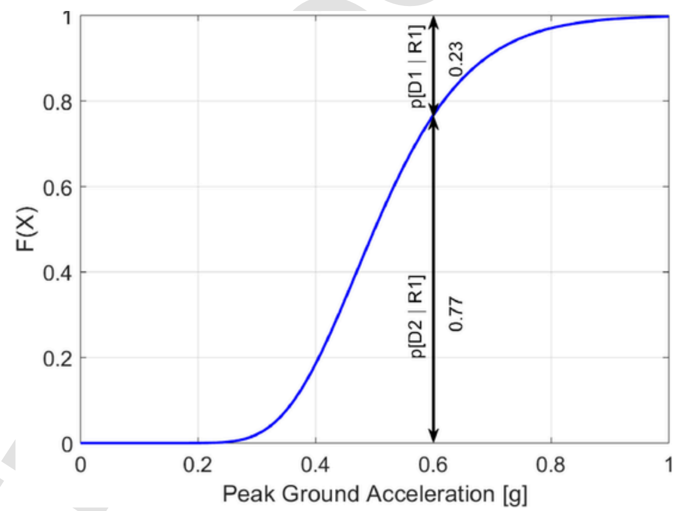

Fig. 3. An example of a fragility function created using a log-normal distribution with $\mu = \log(0.5)$ and $\sigma = 0.25$. At the response $R1 = 0.6$ the probability that the asset will be in damage state *D*1 and *D*2 is 23% and 77% respectively.

also confirmed in the aftermath analysis of the 2001 Nisqually earthquake [10]. Transformers are of special interest because there are many possible modes of failure; one of the more common being failure of transformers and transformer bushings [22].

3. Augmented bus-branch model

Traditional power system models, called "bus-branch" models, fail to model several critical assets inside of the substation. Inside each substation are several elements that are designed to maintain a high level of system reliability. Bus-branch models represents this information as a single asset. While the model is less representative of a real power system the assumption speeds up many types of analyses. An alternative, and much more accurate, power system model is the node-breaker model. While node-breaker models may be more complex, the added granularity is necessary to the study of substation-related contingencies. Recent research has proposed a methodology to convert bus-branch models into node-breaker models for contingency analysis. This, in fact, is an essential step to the study of earthquake resilience. As such, this methodology will be discussed here briefly, but a full treatment of the matters, including a performance validation and comparison, can be found in [14,21].

3.1. Node-Beaker models

Node-breaker models, generally used in energy management software, show the layout and each switching element within the substation (see Fig. 4). System operators use these representative models for real-time monitoring and control of the power system. Transmission planners, on the other hand, tend to utilize bus-branch models because the substation reduction can significantly reduce the number of variables needed to be solved.

In the event that there is a substation related contingency, it is highly unlikely the whole substation is taken out-of-service. Most likely only a few elements would be offline and power would still flow to a some, if not all, feeders.

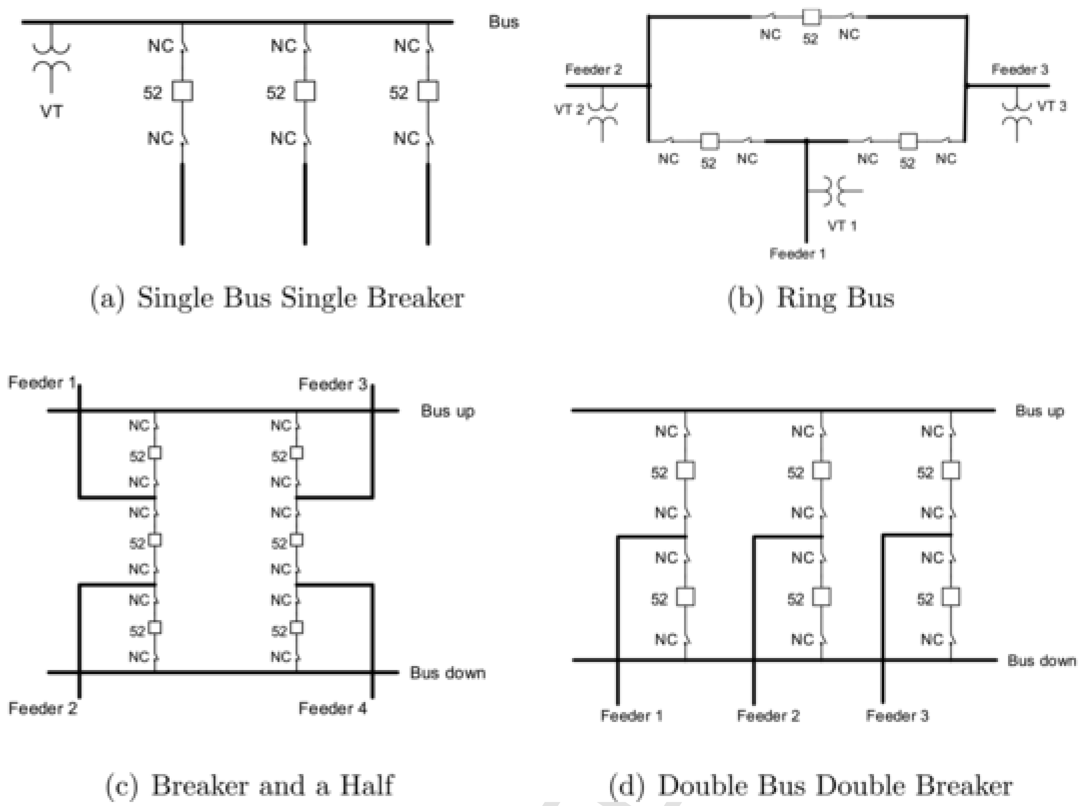

Fig. 4. One line diagram of (a) Single Bus Single Breaker Type Configuration, (b) Ring Bus Configurations, (c) Breaker and a Half Type Configuration and (d) Double Bus Double Breaker Type Configuration [21].

If one wanted to study this scenario, a bus-branch model becomes insufficient. Conversely, since node-breaker models include every switching element, one is able to re-create this scenario and analyze its performance.

3.2. From bus-Branch to augmented bus-Branch models

There exists several software options, e.g., PSS/E, DSATools, PowerWorld, and eTap, that have the capability of node-breaker modeling. PSS/E and PowerWorld, for example, allow the user to create a node-breaker model and then consolidate it based upon the status of each breaker. These consolidated models are representative bus-branch models and are used for various power system analyses. To leverage these tools and to study the effect of substation related outages, a conversion between bus-branch and node-breaker needs to be done in readily-available software. To that end, an "Augmented bus-branch" (a-BB) model was created in which a node-breaker model is represented using elements found in a bus-branch model. Using the methodology provided in [14], buses in the bus-branch model are replaced with substation node-breaker substation models, as shown in Fig. (4), and then each switch-breaker-switch tie is converted into branches with a small impedance. The final result is a model where one can simulate the effect of individual component outages within a substation. An illustration of this process is shown on an example three-bus system in Fig. (5).

4. Analysis of power system resilience

Power system resilience encompasses the entire process of a failure, from response to the eventual repair. This paper assesses the power system's response to damage as it is subjected to various earthquakes. To facilitate this process methods developed in the field of power system reliability to effectively quantify how well the system performs [23] are utilized. The reliability of the power system is quantified using either deterministic or probabilistic methods. Deterministic methods are typically chosen for the low computational cost and their ease of implementation. Unfortunately, the problem of power system seismic resilience is a probabilistic problem. This is due to the fact that each asset – as a response to shaking/liquefaction – will fail based on its own unique fragility function.

To solve the probabilistic reliability problem one can use either analytical or numerical methods. An analytical model represents the power system, and its reliability, as a mathematical model which indicates the structure and relationship between each component. Typically these models are based off Markov models and are solved recursively [24]. The main disadvantage of these methods, however, is that as the system increases in complexity the solution becomes intractable. Numerical methods, on the other hand, use simulations to solve the problem; the most common of which is the Monte Carlo Simulation (MCS) method. While the biggest issue with numerical methods is state selection, MCS solve this problem by randomly sampling the states for either a fixed number of simulations or until some convergence criteria is met. Furthermore, in situations where system complexity is high MCS become extremely useful because they break up probabilistic problem into several deterministic ones.

For these reasons, this research adopts the use of non-sequential MCS methods [25–27] to assess power system resiliency. After each state is randomly created, the power system is checked to see if there are any islanded systems. A power flow analysis is then performed on each, if any, islanded system. It is important to note we are assuming that, after the initial asset failures, each island is now stable. That is, the act of assets failing do not cause any subsequent cascading failures.

The impact that the earthquake will have on the power system is quantified using the Demand Not Served (DNS) metric which is defined as

$$DNS_k = \sum_{i=1}^{m} L_{ik} \tag{7}$$

where L_{ik} is the total demand in the ith island of the kth Monte Carlo sample and m is the total number of islands after the kth sample occurs. Anytime an is-

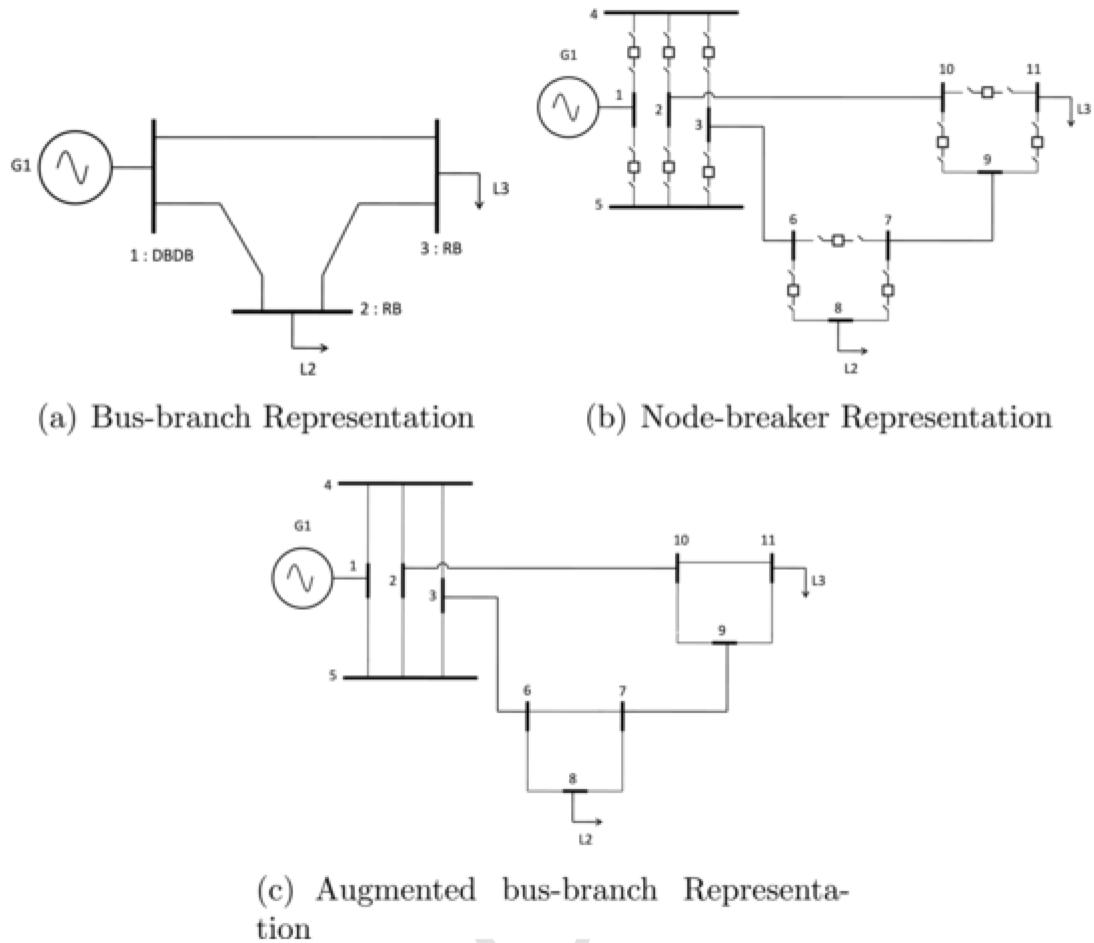

Fig. 5. (a) Bus-branch representation, (b) Node-breaker representation and (c) Augmented bus-branch representation of an example 3-bus system [14].

land would produce a non-converging power flow solution[1] a load-shedding scheme is employed in an attempt to save as much demand as possible. More specifically, the load-shedding scheme used in this paper will incrementally reduce all loads by 10% of their initial value until a converging power flow solution exists or there is no more load to shed. Fig. 6 summarizes the proposed methodology used in this paper.

5. Experimental setup and assumptions

The proposed methodology is applied to the IEEE Reliability Test System 1996 (RTS-96) [29]. This test system consists of 73 buses, 120 transmission lines, and 99 generators with a total capacity of 10,215 MW. Using the protection rules described in Section 3, the augmented RTS-96 (a-RTS) system will consist of 33 DBDB, 26 RB, 10 BAH, and 4 SBSB substations. It is advantageous to use the RTS-96 model to test the methodology because it has three electrically equal areas. This fact is leveraged to mimic a CSZ earthquake scenario by assigning each area of the power system to a representative area of Oregon as depicted in Fig. 7. From left to right, each representative area is labeled as Area 3 (Oregon Coast), Area 2 (Willamette Valley), and Area 1 (East of Cascades).

An earthquake scenario of magnitude 8 ($H1 = 8M$) on the Moment Magnitude Scale (MMS) is simulated on the RTS-96 system with the seismic fault occurring to the left of Area 3. It is assumed that each Area 1, 2, and 3 experiences a response of $R1 = 0.3$ g, $R2 = 0.6$ g, and $R3 = 1.0$ g PGA, respectively. This is to simulate the dampening effect that occurs as an earthquake propagates through the ground. Next, it is assumed there are two different damage states–not damaged ($D1$) or damaged ($D2$)–for each asset in the system. It is assumed that, as a result of the damage, each asset will have two loss states: Operational ($L1$) and non-operational ($L2$). With this in mind it can be said that $p[H \mid A] = 1$ and $p[R \mid H] = I_3$, where I is the identity matrix.

The damage analysis step in the PBEE method, which determines $p[D|R]$, is calculated for breakers, loads, transformers, and generators using (6) with $\sigma = 0.5$ and mean values $\mu = \log(1),\ \log(1.5),\ \log(2),\ \log(2.5)$, respectively. With this assumption, it is implied that the breakers are the most fragile asset and generators are the least. This assignment of asset fragility is observed in historical earthquakes [3]. These fragility curves are shown in Fig. 8. Evaluating these functions at their respective PGA of 1.0 g, 0.6 g, and 0.3 g, the following matrices are obtained

$$\begin{aligned} p[D \mid R]_{Breaker} &= \begin{bmatrix} 0.99 & 0.01 \\ 0.85 & 0.15 \\ 0.50 & 0.50 \end{bmatrix} & p[D \mid R]_{Loads} &= \begin{bmatrix} 1 & 0 \\ 0.97 & 0.03 \\ 0.79 & 0.21 \end{bmatrix} \\ p[D \mid R]_{Transformer} &= \begin{bmatrix} 1 & 0 \\ 0.99 & 0.01 \\ 0.92 & 0.08 \end{bmatrix} & p[D \mid R]_{Generators} &= \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0.97 & 0.03 \end{bmatrix} \end{aligned} \tag{8}$$

Lastly, it is assumed that any non-damaged asset is still fully operational and vice-versa for damaged assets, i.e, $p[L \mid D] = I_2$. Using this and the assumptions listed above, 100,000 MCS for a magnitude 8 earthquake scenario are performed.

[1] Mathematically, a non-converging power flow is likely the result of an ill-conditioned Jacobian matrix which, after a matrix inversion, produces inaccurate results. For further information about possible reasons for non-convergence please see Reference [28].

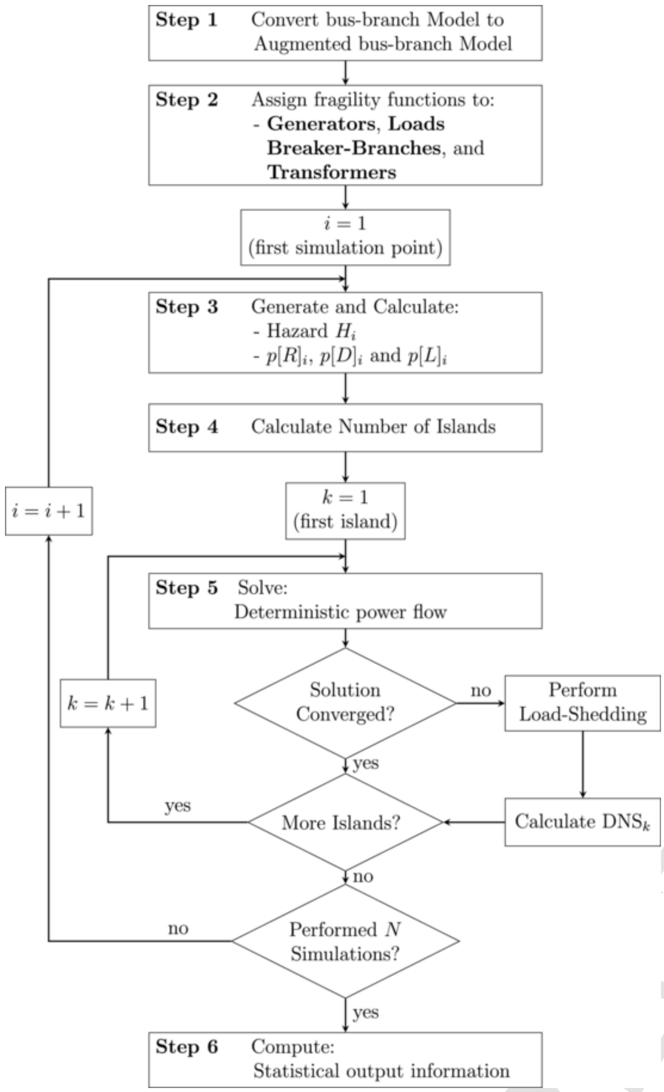

Fig. 6. Flowchart for proposed methodology.

6. Results & discussion

Benchmarking is used to measure the performance of a tool, such as an analysis methodology or a software, using a trusted method and/or dataset, in order to facilitate the comparison of the performance of one tool to another [30]. Comparisons are drawn from existing benchmarking studies performed on the RTS-96 system in reference [31] to determine the validity of the proposed methodology. Each benchmarking study examines the effect of various types of contingencies – specifically cascading outages – on the RTS-96 system. For example, in the DC Oak Ridge-PSERC-Alaska (OPA) methodology it is assumed that each transmission line has a 1% failure probability. After a DC power flow is performed the subsequent cascading failure is then examined whenever a transmission line exceeds 99% of its rated capacity. In addition to synthetic data, historical outage data for the North American Western Electricity Coordinating Council (WECC) region is used for further comparisons [32]. Each of these benchmarking datasets are used to determine if the output of the proposed methodology contains any similarities, such as shape. Furthermore, even if the mode of failure may be different, it is important to compare earthquake model used in this research with that of other simulated large scale outages.

The cumulative probability distributions shown in Fig. 9 display the differences and similarities between each models' output. The plot shown here is constructed in such a way to show that as the percent of demand loss increases (shown in p.u.), the cumulative probability decreases. For example, at values close to 1 p.u. demand loss, the probability that the system will lose more load approaches zero. This indicates that it is unlikely that there would be total system failure. One similarity shared between each plot is the exponential trend in demand loss.

However, a more direct comparison of our proposed methodology can be made with the historical data (red trace in Fig. 9) because of the heavy tail. In the historical plot, the heavy tail is the result of limited WECC outage data at high level of demand loss. The proposed method, on the other hand, has a heavy tail because some outage scenarios produce a non-converging power flow solution. Another interesting comparison can be made to the PRACTICE dataset (violet trace). In the PRACTICE plot, a stair-step trend is seen where, in several ranges of lost demand, the probability does not decrease. This is because of the load-shedding schemes implemented in their model which tends to drop whole loads versus small percentages. This is contrast to the presented method in which the load is homogeneously decreased until all the loads have been removed. As a result, the presented results show a similar stair-step trend but only slightly less so than in the PRACTICE data set.

In an effort to measure the robustness of the presented model a different test case is analyzed in which we upgrade and degrade several assets in the system. As stated above, the most fragile components tend to be breaker branches with loads being the next most fragile asset. Therefore, these should be seismically reinforced first. While it makes sense in the presented model to retrofit breaker branches, upgrading a load makes little sense because at the transmission level a load model typically represent an aggregate of several population centers and may include relatively large cities. The most realistic seismic retrofits then becomes breakers and transformers. The effect of upgrading and downgrading these assets is simulated by decreasing and increasing the failure probabilities of these assets by an fixed 25% respectively. Results for these simulations are shown in Fig. 10 and Table 1.

For lower levels of demand loss the seismic upgrades and downgrades tend to have the desired effect whereby increasing resiliency decreases the probability of demand being lost. However, an interesting observation is that decreasing the asset failure probability increases the overall risk to the system because of the increased probability of larger outages as observed in the Fig. 10. These results suggest that a decrease in overall risk may actually require an increase in failure rate of some assets. This phenomena can be described through the understanding of ductile and brittle systems. In the context of seismic resilience, a ductile system will tend to restrict the initial shaking and deform without complete failure. Although the effect of cascading failures is not modeled, it is likely that initial early failures actually provide a form of load shedding, thus protecting the core system from complete failure. A brittle system, on the other hand, resists any failure at low seismic levels, but when it does fail at higher levels, it tends to fail completely. This topic was discussed in the analysis of the Nisqually Earthquake [10] and it was suggested that a system with higher seismic resilience is one that is more ductile. This effect is quantitatively observed for our model in Table 1. By breaking the system into many small sized islands, the system is therefore able to serve more customers.

7. Conclusion

Previous studies in seismic reliability analysis of an electrical transmission system present the probability of loss of individual assets using site specific ground motion. In this paper, an augmented bus-branch model has been proposed to enable the study of electrical system earthquake resilience. Assets of particular interest are breakers, loads, transformers, and generators. Leveraging the PBEE method, each asset in the augmented model has a fragility function which describes its response to shaking. As a proof a concept, the RTS-96 is used and the failure of each asset is sampled using a Monte Carlo method. Experimental results to historical data and benchmarking studies which examine the effect of cascading outages on the RTS-96. Results show comparative exponential trends with the benchmarking methods and the heavy tail of the historical data sets.

Model robustness is analyzed by seismically enhancing and weakening assets in the system. The results suggest that a system with

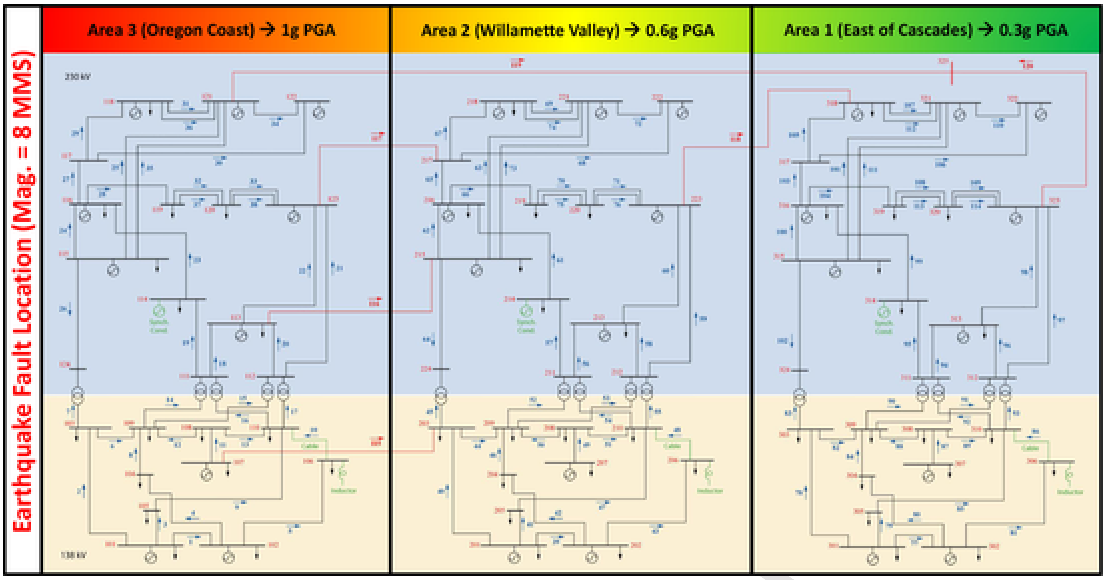

Fig. 7. Depiction of the earthquake scenario simulated on the IEEE RTS-96 system. For this scenario, a magnitude 8 on the Moment Magnitude Scale (MMS) occurs to the left (west) of Area 3–representing the Oregon Coast. This causes an assumed corresponding ground shaking of 1 PGA, 0.6 PGA, 0.3 PGA for Area 3, Area 2, and Area 1, respectively.

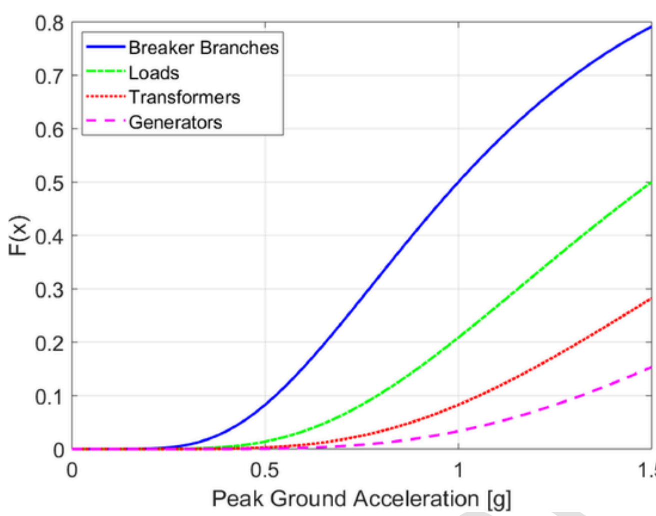

Fig. 8. Fragility functions for four different types of assets: breaker branches (blue), loads (green), transformer branches (red), and generators (magenta). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

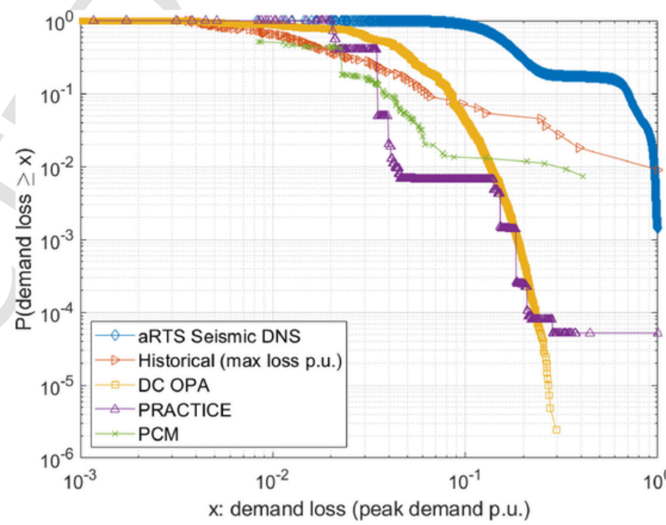

Fig. 9. Cumulative probability distribution of demand loss. A full overview of the Historical, DC OPA, PRACTICE, and PCM methods and results can be found in [30].

has a decreased risk of large outages due to earthquakes. The trade-off, however, is that there is higher probability of a lower DNS scenario occurring when the asset failures has been increased. This can be understood in the study of ductile and brittle systems. With respect to earthquakes, making assets fail gracefully results in a power system that is ductile which responds to ground shaking better than a brittle one. This idea has been discussed in the past in a post-event analysis of the Nisqually earthquake which occurred in 2001 but the effect of this on power systems had not been fully explored.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests

CRediT authorship contribution statement

Brandon Johnson: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Vishvas Chalishazar:** Conceptualization, Software, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Eduardo Cotilla-Sanchez:** Conceptualization, Writing - original draft, Writing - review & editing, Funding acquisition. **Ted K.A. Brekken:** Conceptualization, Writing - original draft, Writing - review & editing, Funding acquisition.

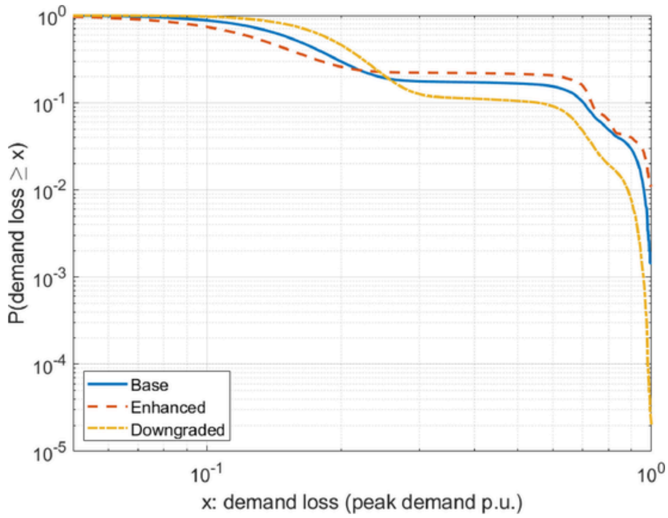

Fig. 10. Cumulative probability distributions for the augmented RTS model with base, seismically robust (enhanced) assets, and seismically weaker (downgraded) assets.

Table 1
Statistical measures for the base, enhanced, and downgraded augmented RTS model.

	DNS [p.u.]	Number of Islands†	Buses per Island†	
Base	μ	0.25	10	50
	σ	0.24	3	21
Enhanced	μ	0.26	4	139
	σ	0.27	2	91
Downgraded	μ	0.24	19	24
	σ	0.17	4	5

† Rounded to the nearest whole number

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