SAND2021-13043C

Winter Storm Scenario Generation for Power Grids Based on Historical Generator Outages

Brent Austgen*, Manuel Garcia†, Brian Pierre†, John Hasenbein*, and Erhan Kutanoglu*

*Operations Research & Industrial Engineering
Cockrell School of Engineering
The University of Texas at Austin
Austin, USA
brent.austgen@utexas.edu

†Electric Power Systems Research
Sandia National Laboratories
Albuquerque, USA
mgarc19@sandia.gov

***Abstract*—We present a procedure for randomly generating realistic steady-state contingency scenarios based on the historical outage data from a particular event. First, we divide generation into classes and fit a probability distribution of outage magnitude for each class. Second, we provide a method for randomly synthesizing generator resilience levels in a way that preserves the data-driven probability distributions of outage magnitude. Finally, we devise a simple method of scaling the storm effects based on a single global parameter. We apply our methods using data from historical Winter Storm Uri to simulate contingency events for the ACTIVSg2000 synthetic grid on the footprint of Texas.**

***Index Terms*—contingency, inverse transform sampling, maximum likelihood estimation, Monte Carlo method, power generation, power system planning, scenario generation, winter storms, Winter Storm Uri**

I. Introduction

Natural disasters such as hurricanes, fires, and winter storms are increasing in frequency, and their effects are motivating investment in power system resilience. Winter Storm Uri, which occurred in February 2021, was particularly devastating to the state of Texas and, at its peak, resulted in approximately 10 million Texans losing access to electricity [1]. Texas now faces the task of overseeing winterization investments. These low-probability high-consequence events are difficult to assess in risk-averse decision-making. This two-part paper addresses this problem in the context of winter storm planning. This paper serves as Part I and its purpose is to quantify the uncertainty of a winter storm event by creating probabilistic scenarios based on historical data. Part II uses these scenarios to formulate and solve a risk-averse scenario-based two-stage stochastic optimization problem [2].

The unprecedented cold, snow, and ice brought on by Winter Storm Uri in February 2021 induced similarly unprecedented consequences for the infrastructure and people of Texas. The Electric Reliability Council of Texas (ERCOT) anticipated 14 GW of generation outages and peak demand of 67.2 GW in its extreme winter planning scenario [1]. At the peak of Uri, generator outages exceeded 50 GW and demand rose to an estimated 76.8 GW. However dire, these circumstances were far preferable to the possibly months-long blackout that ERCOT officials described as being “seconds and minutes” away.

Researchers have identified several causes of this catastrophic failure. Those include insufficient winterization of grid components, compounding failures between natural gas and power grid infrastructure, and the isolation of the Texas Interconnection from the rest of the United States and Mexico [1]. Moving forward, policymakers may seek to be informed by system-level models that account for these factors, and this should motivate researchers to develop such models and moreover identify data to drive them. Unfortunately, comprehensive data for actual power grids are typically kept private for sake of security. To remedy this problem for researchers, Gegner *et al.* developed a collection of realistic synthetic power grids spanning the conterminous United States [3].

Synthetic grids serve well as surrogates for actual grids in model development and validation, but it is challenging to develop realistic natural hazard contingencies for a synthetic grid. The reasons for this include the complexities of weather and resilience modeling, the lack of data due to the infrequency of extreme weather events, and the general difficulties that arise in applying real-world effects to fictitious elements. Some examples of contingency scenario generation are the use of fragility curves to model the effects of strong winds on the IEEE 118-bus grid [4] and the use of hydrological modeling to assess the effects of hurricane flooding on the ACTIVSg2000 grid [5], [6]. Related to extreme winter storms, there is also the work of Pierre *et al.* which employs synthesized probability distributions for the failure rates of lines, transformers, buses, and generators in the RTS-96 grid [7].

In this work, we describe a method for randomly generating sets of mutually consistent winter storm scenarios. Our method is not grounded in weather modeling like the examples just mentioned, but rather on empirical outage data. The remainder of this work is organized as follows. In Section II, we describe a scheme for generator classification and a means of modeling an outage distribution for each class from empirical data. In Section III, we propose a method of synthesizing winter storm resilience information for each generator to ensure consistency across scenarios. We present a method for scaling the severity of storm effects in Section IV. Section V describes an application of our method to produce scenarios for the synthetic ACTIVSg2000 grid using empirical data from Winter Storm Uri. Finally, Section VI summarizes potential research directions.

II. Modeling Generator Outages/Derates

For sake of brevity, the term “outage” is overloaded in this work to encompass both outage and derate events, and the term “magnitude” is used to describe an amount of lost generation capacity. We assume that the magnitude of a generator unit’s outage is a function of three primary factors: fuel type, local temperature, and resilience to cold weather. In general, generator fuel type and historical temperature

This work was supported by the Laboratory Directed Research and Development program at Sandia National Laboratories and the Energy Institute at the University of Texas at Austin. Sandia National Laboratories is a multimission laboratory managed, and operated by the National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy’s National Nuclear Security Administration under Contract DE-NA0003525.

data are readily available. As a first step, we partition the generator units into a set of classes $\mathcal{C}$ based on fuel type and temperature. Public data pertaining to generator resilience is more elusive, and it is difficult to quantify resilience anyway using such data. Though we consider cold weather resilience a primary factor, we handle it differently in the uncertainty model as discussed in Section III.

Following classification, we fit a distribution of generator outage magnitude for each class. We limit our scope to modeling generator unit outages at the time of the peak system outage. As a means of normalization, we divide the absolute outage magnitude of each generator unit by its maximum capacity to obtain relative outage magnitude. In choosing the form of distribution to estimate, we consider that each generator unit has two natural thresholds: the ability to withstand weather conditions up to some limit before suffering an outage and the inability to lose more than its maximum capacity. These thresholds differ unit to unit, so it reasons that a considerable number of units experience either no outage or total outage at the peak of a winter storm. For each class $c \in \mathcal{C}$, we model the relative outage uncertainty as a mixed random variable X_c. The distribution of X_c has probability p_c of no outage and probability q_c of total outage with partial outages following a density function $G_c(x)$. With $H(\cdot)$ denoting the Heaviside step function, the CDF for X_c is

$$F_c(x) = p_c H(x) + (1 - p_c - q_c) G_c(x) + q_c H(x - 1) \quad (1)$$

which is characterized by p_c, q_c, and the parameters of $G_c(x)$. The choice of $G_c(x)$ and exact means of estimating the parameters are left for the modeler to decide, though we provide an example in Section V.

III. Modeling Generator Resilience

It reasons that a generator's resilience to winter storms should be an important factor in our uncertainty model, but the distributions developed in the previous section are unconditional with respect to resilience. Treating each unconditional distribution as the marginal of a joint bivariate distribution whose second dimension is resilience, we remedy this problem by decomposing each distribution into a discrete set of (weighted) conditional distributions. In so doing, we establish a basis for randomly assigning a resilience level and associated conditional distribution to each synthetic generator. Importantly, our scheme ensures the conditional distributions preserve the original unconditional distribution through the law of total probability. Though we treat generator resilience as a random variable, we do so solely for the sake of modeling. We do not view resilience as being random from a practical perspective, and if we were to study a real grid, then we would use the known resilience details to support the development of generation classes described in Section II. However, we are studying synthetic grids with unspecified resilience details.

Recall that our intention is to use the manufactured scenarios in a stochastic programming optimization model meant to inform winterization investments. In that context, modeling generator resilience adds value – it allows us to assess if the optimal investment strategy focuses more on generators of higher or lower resilience.

A. Abstract Model of Generator Resilience

For each generation class we model generator resilience as a second random variable Y and suppose the existence of a joint distribution with PDF $f(x, y)$ and CDF $F(x, y)$. Our proposed method of resilience synthesis is based on the following observation. Let X be a generic random variable with support Ω and CDF $F(x)$ and consider a function $T(z)$ nondecreasing on the unit interval and satisfying $T(0) = 0, T(1) = 1$. Then $T(F(x))$ is likewise a valid CDF for some other random variable.

For sake of simplicity, we assume the support of Y is a discrete set $\mathcal{N}$. Following the aforementioned observation, we synthesize conditional CDFs as transformations of the marginal CDF of X, i.e.,

$$F(X \mid Y = i) = T_i(F_X(x)) \quad (2)$$

for all $i \in \mathcal{N}$ such that the likelihood of sampling certain events is perturbed according to generator resilience. The synthesized conditional CDFs should preserve the marginal through the law of total probability, and this requires mutual consideration of the marginal probabilities $\pi_i = f_Y(i)$ where f_Y is the marginal PDF of Y. Letting $T(z)$ be the probability-weighted sum of transformations, we seek to select T_i and π_i such that

$$T(F_X(x)) = \sum_{i \in \mathcal{N}} \pi_i T_i(F_X(x)) = F_X(x), \quad (3)$$

for all $x \in \Omega$ which is equivalent to requiring

$$T(z) = \sum_{i \in \mathcal{N}} \pi_i T_i(z) = z \quad (4)$$

for all $z \in [0, 1]$. Of course, the constraints $\sum_{i \in \mathcal{N}} \pi_i = 1$ and $\pi_i > 0$ for all $i \in \mathcal{N}$ must also hold.

B. Concrete Model of Generator Resilience

Any set of CDFs each with unit interval support that satisfy (4) may comprise the set of transformations. However, it is desirable for the transformations to also be strictly monotonic. This property ensures that any generator, regardless of its resilience level, may realize any outage outcome from the unconditional distribution. Intuitively, transformations that are not strictly monotonic attribute too much of the outage uncertainty to generator resilience. For example, a planned outage might cause a grid's most resilient generator to be completely offline when a storm occurs. For this reason, we do not want to prohibit generators from experiencing certain outcomes.

We propose using a particular set of beta CDFs since they satisfy all the required conditions and are moreover each strictly monotonic on the unit interval. The beta distribution is characterized by two parameters α and β, and for integer-valued $\alpha, \beta > 0$ its PDF is

$$f(z; \alpha, \beta) = (\alpha + \beta - 1) \binom{\alpha + \beta - 2}{\alpha - 1} z^{\alpha - 1} (1 - z)^{\beta - 1}. \quad (5)$$

Now for fixed n, we let $\mathcal{N} = \{0, \ldots, n\}$ be the set of $n + 1$ resilience levels. For all $i \in \mathcal{N}$, we let $\pi_i = \frac{1}{n+1}$ and

$$\begin{aligned}
T_i(z) &= \int f(z; n - i + 1, i + 1)\, dz \\
&= \int (n + 1) \binom{n}{i} z^{n-i} (1 - z)^i \, dz \\
&= \int \sum_{j=0}^{i} (n + 1) \binom{n}{i} \binom{i}{j} (-1)^{i+j} z^{n-j} \, dz \\
&= \int \sum_{j=0}^{i} (n + 1) \binom{n}{j} \binom{n - j}{n - i} (-1)^{i+j} z^{n-j} \, dz \\
&= \sum_{j=0}^{i} \frac{n + 1}{n - j + 1} \binom{n}{j} \binom{n - j}{n - i} (-1)^{i+j} z^{n-j+1} \\
&= \sum_{j=0}^{i} \binom{n + 1}{j} \binom{n - j}{n - i} (-1)^{i+j} z^{n-j+1}.
\end{aligned} \quad (6)$$

The third equality follows from applying the binomial theorem to $(1 - z)^i$, the fourth from a combinatorial identity, the fifth from the constant of integration being zero given the known condition $T(0) = 0$, and the sixth from another combinatorial identity.

It remains to verify the selection of $T_i(z)$ from (6) and $\pi_i = \frac{1}{n+1}$ preserves distributions per (4). Indeed,

$$\begin{aligned} T(z) &= \sum_{i \in \mathcal{N}} \pi_i T_i(z) \\ &= \sum_{i=0}^{n} \frac{1}{n+1} \sum_{j=0}^{i} \binom{n+1}{j} \binom{n-j}{n-i} (-1)^{i+j} z^{n-j+1} \\ &= \sum_{j=0}^{n} \left(\sum_{i=j}^{n} \binom{n-j}{n-i} (-1)^i \right) \binom{n+1}{j} \frac{(-1)^j z^{n-j+1}}{n+1} \\ &= z. \end{aligned} \tag{7}$$

This verification hinges on switching the order of the sums. In so doing, we obtain an inner sum in the second-to-last equality that is an alternating sum of binomial coefficients. That sum is identically 0 for $0 \leqslant j \leqslant n-1$ (i.e., the coefficients of $z^{n+1}, z^n, \ldots, z^2$ in $T(z)$ are all 0). For $j = n$, the inner sum is either -1 or 1 for n odd or even, respectively, and its product with the other expressions in the outer sum is 1. Thus, the coefficient of z in $T(z)$ is 1.

IV. Modeling Severity of Storm Effects

Our model of uncertainty does not explicitly capture the severity of the storm but rather its effect on generator outages. This is sufficient for our purposes and perhaps even ideal since, under some measures of storm severity, more severe storms might not induce worse outages. We propose modeling the severity of storm effects relative to those of the storm from which the outage distributions are constructed.

More specifically, for generation class c let $\boldsymbol{\lambda}_c$ be the vector of parameters for the distribution of X_c. We use a single scalar r to model severity and a function $S_c(r, \boldsymbol{\lambda}_c)$ for each class c to model its effects on the distributions. That is, we define $\widehat{\boldsymbol{\lambda}}_c = S_c(r, \boldsymbol{\lambda}_c)$ to be the parameters of a perturbed random variable $\widehat{X}_c$ corresponding to severity r. We further propose having r be a realization of a random variable R representing the uncertainty of storm effects. This is not a necessary measure, and one could produce a set of scenarios of the same severity by choosing R to be a degenerate random variable.

Our proposed approach is simple in that the perturbation of each class of generation is a function of the single parameter r. The approach is also deliberately abstract so that a modeler may embed his or her own beliefs about severity through R and $S_c(\cdot)$ for $c \in \mathcal{C}$. For example, one might want the mean of the resulting distribution to be monotonic in r or for $r = 1$ to represent no change in severity.

In many cases, winter storms also affect demand – households with electric heaters are likely to use more energy to keep warm as temperatures drop. In Section V, we present a specific implementation of R and $S_c(\cdot)$, $c \in \mathcal{C}$ and additionally discuss a method for modeling the system load as a function of r.

V. Application

In this section, we walk through an application of the methodology outlined in Sections II, III, and IV to the ACTIVS 2000-bus synthetic grid on the footprint of Texas. The first three subsections that follow correspond to each of those three sections. In the fourth and final subsection, we discuss a Monte Carlo sampling approach and properties of the scenarios we sampled.

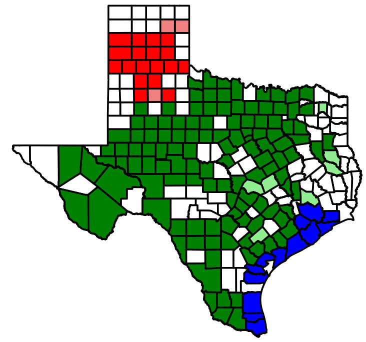

Fig. 1. The geographical zones we used to classify generation. The panhandle zone is colored red, the coastal zone blue, and elsewhere green. Dark shades indicate counties with generators on the ERCOT grid. Light shades indicate the manually labeled counties in which the synthetic grid has generators but the ERCOT grid does not.

A. Generator Outages/Derates

Following Winter Storm Uri, ERCOT published data on the generator outage events that occurred during the event [8]. We filtered the outage samples to only those in effect at the time of the peak system outage, February 15 at 7:35AM, then normalized the samples to make them proportions of the generator nameplate capacities. Using fuel type directly and location indirectly as a rough proxy for temperature, we devised a set of classes $\mathcal{C}$ in which to partition the generators. Fig. 1 illustrates the geographical zones we used for classification, and the eight classes we devised are listed in Table I.

To finish assembling the data needed to fit the outage distributions, we estimated the number of generators that did not experience an outage using data from ERCOT's December 2020 Capacity, Demand, and Reserves (CDR) report [9] and ERCOT's report on the causes of generator failures during Uri [10]. We accounted for generators already offline prior to Uri in this estimation.

We let $G_c(x)$ from Section II be a Johnson's S_B-distribution. The distribution has four parameters – two to define the boundaries of the open support interval, and another two parameters a_c and b_c to define the shape. Fixing the support set to the unit interval and heeding its openness, the CDF may be represented for $x \in \mathbb{R}$ as

$$G_c(x) = \begin{cases} 0, & x \leqslant 0 \\ \Phi\left(a_c + b_c \log\left(\frac{x}{1-x}\right)\right), & 0 < x < 1 \\ 1, & 1 \leqslant x \end{cases} \tag{8}$$

where $\Phi(\cdot)$ is the standard normal CDF. The corresponding $F_c(x)$ from (1) is characterized by $\boldsymbol{\lambda}_c = (p_c, q_c, a_c, b_c)$. From our complete set of relative outage samples, we estimated these parameters for each class $c \in \mathcal{C}$. We present our estimates in Table I and illustrate the distributions in Fig. 2. We computed p_c and q_c exactly as proportions of generators experiencing no outage and total outage, respectively, and we computed a_c and b_c using the maximum likelihood estimation (MLE) tools from the SciPy statistics module [11].

B. Generator Resilience

To synthesize the conditional CDFs, we applied the transformations from (6) with weights $\pi_i = \frac{1}{n+1}$ for $\mathcal{N} = \{0, 1, 2, 3\}$. We illustrate these transformations and their application to the non-panhandle wind marginal distribution in Fig. 3. In this example, we see from the marginal CDF in the lower right subplot that a non-panhandle wind

TABLE I
ESTIMATED DISTRIBUTION PARAMETERS BY GENERATION CLASS

c	p_c	q_c	a_c	b_c
Gas, Non-Coastal	0.5171	0.2976	0.7346	0.9005
Gas, Coastal	0.1389	0.7778	0.8418	0.7608
Wind, Non-Panhandle	0.3000	0.1963	-0.8647	0.5429
Wind, Panhandle	0.5143	0.0000	0.9381	0.7892
Coal, All	0.4444	0.2778	0.4648	0.9325
Nuclear, All	0.7500	0.2500	-	-
Solar, All	0.8118	0.0235	-0.4329	1.0771
Hydro, All	0.9091	0.0909	-	-

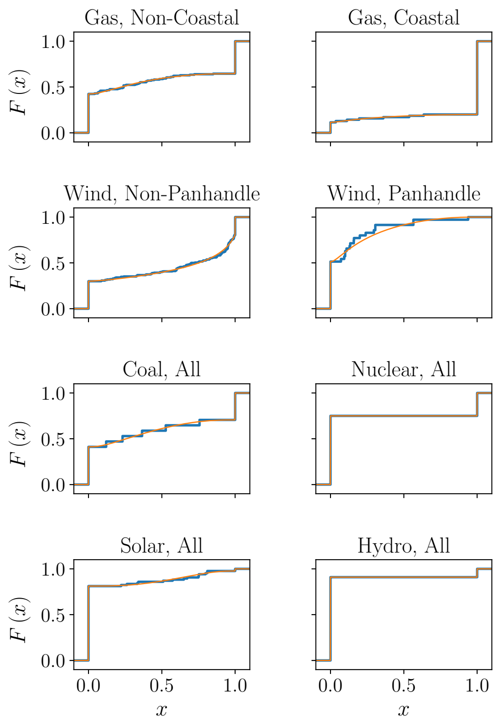

Fig. 2. The empirical distributions of Winter Storm Uri outages are shown in blue and our estimated mixed distributions in orange.

generator in general has a 39.8% probability of having up to a 50% outage. As evidenced by the synthesized conditional CDFs shown in the upper right subplot, the conditional probabilities of the same event are 86.8%, 52.1%, 17.6%, and 2.5% for increasing resilience levels $i \in \{0, 1, 2, 3\}$, respectively.

C. Severity of Storm Effects

In Section IV, we described a deliberately abstract approach to modeling the severity of storm effects, and now we present a specific implementation. To capture the severity of storm effects, we modeled each $S_c(\cdot)$ by the following perturbations:

$$\hat{p}_c = 1 - \min\{r, \tfrac{1}{1-p_c}\}(1 - p_c), \quad (9)$$

$$\hat{q}_c = \min\{r, \tfrac{1}{1-p_c}\}q_c, \quad (10)$$

$$\hat{a}_c = a_c, \quad (11)$$

$$\hat{b}_c = b_c. \quad (12)$$

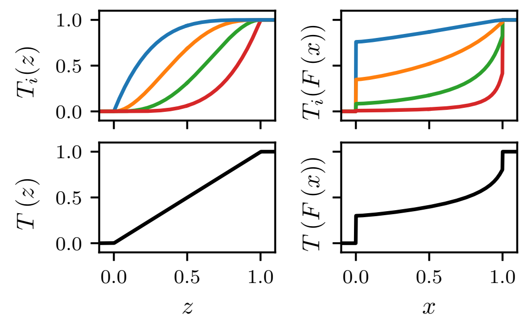

Fig. 3. A set of four beta CDF transformations are shown in the upper left. The lower right plot shows the marginal distribution for non-panhandle wind outages, and the upper right plots show the application of the transformations to that distribution. The lower left plot illustrates that the probability-weighted sum of the transformations is indeed $T(z) = z$ for $0 \leqslant z \leqslant 1$.

These perturbations affect only the probability of no outage, the probability of total outage, and consequently the probability of partial outage. We were motivated to use these perturbations for two main reasons. First, $\widehat{\boldsymbol{\lambda}}_c = \boldsymbol{\lambda}_c$ when $r = 1$. Second, $\mathbb{E}[\widehat{X_c}] = 0$ and more precisely $\widehat{X}_c = 0$ when $r = 0$. Finally, the perturbations ensure that $\mathbb{E}[\widehat{X}_c]$ is monotonic and moreover piecewise linear in r for each generation class. The piecewise linearity follows from the pointwise minimums which serve to ensure the perturbed parameters remain valid. The parameters $\hat{p}_c$ and $\hat{q}_c$ are linear in r for $0 \leqslant r \leqslant \frac{1}{1-p_c}$ and constant for $r > \frac{1}{1-p_c}$.

Establishing $r = 1$ as having no change in effect allowed us to control the probability of realizing a winter storm more severe than Uri. To model a wide variety of winter storm effects, we chose for R to follow a beta prime distribution with $P(R > 1) = 0.01$ and a mode of $r = 0.50$. Since we devised eight classes each with a distinct p_c, the expected system-wide outage is a piecewise linear function of r with nine intervals. The "left-most" interval is $r \in [0, \min_{c \in \mathcal{C}} \frac{1}{1-p_c}] \approx [0, 1.1613]$ which accounts for more than 99.8% of the severity distribution.

D. Sampling

We applied the synthesized conditional distributions to the ACTIVSg2000 synthetic grid on the footprint of Texas [3]. The grid features 432 in-service generators sited at 168 of the total 1250 substations. In lieu of generator coordinate data, we associated each generator with the coordinates of the substation to which it connects. Using this information, we assigned a class $c \in \mathcal{C}$ to each of the synthetic generators.

Synthesizing the conditional CDFs as proposed permitted straightforward sampling via inverse transform method. We outline the complete generic procedure for generating scenarios in Fig. 4. In that procedure, $\mathcal{C}$ denotes the set of generator classes, Ω the set of scenarios to produce, and G_c the number of class c generators in the grid. We add indices to the marginal CDF $F(x)$, the set of resilience levels $\mathcal{N}$, the weights π_i, and the transformations $T_i(z)$ to indicate they may vary by generation class. Those are otherwise as generically defined in Section III. Additionally, r, R, $\boldsymbol{\lambda}_c$, $\widehat{\boldsymbol{\lambda}}_c$, and $S_c(\cdot)$ are as generically defined in Section IV. Finally, by $U(0, 1)$ we denote the uniform continuous distribution with unit interval support. The outputs are a vector of sampled severities $[r_\omega]$, a vector of sampled generator resilience levels $[y_g]$, and a matrix of sampled relative outage magnitudes $[x_{gs}]$.

for $\omega \in \Omega$ **do**
  $r_\omega \leftarrow$ random sample from distribution of R
end for
for $c \in \mathcal{C}$ **do**
  for $g \in G_c$ **do**
    $y_g \leftarrow$ random sample from $\{\pi_{i,c}, i \in \mathcal{N}_c\}$
    for $\omega \in \Omega$ **do**
      $\widehat{\boldsymbol{\lambda}}_c \leftarrow S_c(r_\omega, \boldsymbol{\lambda}_c)$
      $u \leftarrow$ random sample from $U(0,1)$
      $z \leftarrow T_{i,c}^{-1}(u)$
      $x_{g,\omega} \leftarrow F_c^{-1}(z; \widehat{\boldsymbol{\lambda}}_c)$
    end for
  end for
end for

Fig. 4. The procedure for generating scenarios via inverse transform sampling of the synthesized conditional CDFs.

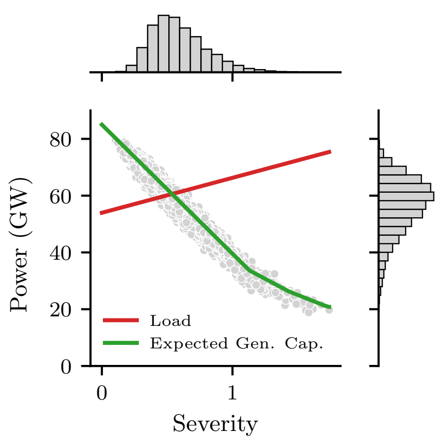

Fig. 5. The joint distribution of severity and system-wide operational generation capacity from 10000 Monte Carlo simulations. The green and red lines, respectively, represent the expected system-wide operational generation capacity and system-wide load as a function of severity.

In addition to steady-state case study parameters, the ACTIVSg2000 grid dataset supplies time series data for dynamic analysis [12], [13]. Particularly, it supplies hourly load data for each bus for a full a year. For this grid specifically, we also scaled the load at each bus according to the sampled severity to capture customers demanding more power to heat their homes. To do this, we identified the winter peak load in the time series and associated it with severity $r = 0$. The projected peak demand during Uri was approximately equal to ERCOT's peak summer demand in 2020 [1], [9]. Considering this, we scaled the winter peak load of 53.96 GW to match the summer peak load of 66.28 GW in magnitude and associated this amplified load with a severity of $r = 1$. For severities other than $r = 0$ or $r = 1$, we linearly extrapolated the magnitude of the load from these two points. We illustrate the relationship between severity and system-wide operational generation capacity and load in Fig. 5. The figure also illustrates the 10000 sample storms we use for model optimization and validation in Part II of this work [2].

VI. Future Work

We have identified three directions of improvement for winter storm scenario generation. First, our method depends partly on empirical data and partly on fabricated data. It would be ideal to eliminate the dependence on fabricated data by acquiring a suitable generator resilience data source from which the bivariate distributions could be directly estimated. Second, recall from Section II that we employed generator unit location as a proxy for weather in our classification scheme. We are interested in alternatively performing classification based on generator fuel type alone, and introducing historical temperature data as a third dimension in the joint distribution for each class. While there are more factors to consider in fitting a multidimensional joint distribution, we expect that the historical temperature data at least could be easily obtained. Third and finally, our method is limited in that it focuses on a single instant in time, but it is common in resilience studies to incorporate a time factor. The ERCOT outage data indicates that Uri caused many generators to experience intermittent outages, and it would be interesting to study a stochastic model in which the scenarios capture such behaviors.

References

[1] J. W. Busby *et al.*, "Cascading risks: Understanding the 2021 winter blackout in texas," *Energy Research & Social Science*, vol. 77, p. 102106, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629621001997

[2] M. Garcia, B. Austgen, B. Pierre, J. Hasenbein, and E. Kutanoglu, "Risk-averse investment optimization for power system resilience to winter storms," in *2022 IEEE Power Engineering Society Transmission and Distribution Conference (Submitted as Part II of this paper)*. IEEE, 2022.

[3] K. M. Gegner, A. B. Birchfield, T. Xu, K. S. Shetye, and T. J. Overbye, "A methodology for the creation of geographically realistic synthetic power flow models," in *2016 IEEE Power and Energy Conference at Illinois (PECI)*, 2016, pp. 1–6.

[4] M. Sahraei-Ardakani and G. Ou, "Day-ahead preventive scheduling of power systems during natuaral hazards via stochastic optimization," in *2017 IEEE Power Energy Society General Meeting*, 2017, pp. 1–1.

[5] B. Austgen, E. Kutanoglu, and J. Hasenbein, "Impacts of approximate power flow models on optimal flood mitigation in a stochastic program," in *Proceedings of the 2021 IISE Annual Conference*, A. Ghate, K. Krishnaiyer, and K. Paynabar, Eds., May 2021.

[6] A. Shukla, E. Kutanoglu, and J. Hasenbein, "A scenario-based optimization approach for electric grid substation hardening against storm surge flooding," in *Proceedings of the 2021 IISE Annual Conference*, A. Ghate, K. Krishnaiyer, and K. Paynabar, Eds., May 2021.

[7] B. J. Pierre, B. Arguello, A. Staid, and R. T. Guttromson, "Investment optimization to improve power system resilience," in *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2018, pp. 1–6.

[8] (2021) Generator resource and energy storage resource outages and derates for february 10-19, 2021. Electric Reliability Council of Texas. [Online]. Available: http://www.ercot.com/news/february2021

[9] (2020) Capacity, demand and reserves report december 2020. Electric Reliability Council of Texas. [Online]. Available: http://www.ercot.com/gridinfo/resource

[10] (2021) Ercot winter storm generator outages by cause updated report. Electric Reliability Council of Texas. [Online]. Available: http://www.ercot.com/news/february2021

[11] P. Virtanen *et al.*, "SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python," *Nature Methods*, vol. 17, pp. 261–272, 2020.

[12] H. Li, A. L. Bornsheuer, T. Xu, A. B. Birchfield, and T. J. Overbye, "Load modeling in synthetic electric grids," in *2018 IEEE Texas Power and Energy Conference (TPEC)*, 2018, pp. 1–6.

[13] H. Li, J. H. Yeo, A. L. Bornsheuer, and T. J. Overbye, "The creation and validation of load time series for synthetic electric power systems," *IEEE Transactions on Power Systems*, vol. 36, no. 2, pp. 961–969, 2021.