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Dongqi Wu
Texas A&M University https://orcid.org/0000-0002-0238-6088
Xiangtian Zheng
Texas A&M University https://orcid.org/0000-0003-2884-3213
Yixing Xu
Breakthrough Energy
Daniel Olsen
Breakthrough Energy
Bainan Xia
Breakthrough Energy
Chanan Singh
Texas A&M University
Le Xie (le.xie@tamu.edu)
Texas A&M University https://orcid.org/0000-0002-9810-948X

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An Open-source Model for Simulation and Corrective Measure Assessment of the 2021 Texas Power Outage

Dongqi Wu[1,†], Xiangtian Zheng[1,†], Yixing Xu[2], Daniel Olsen[2], Bainan Xia[2], Chanan Singh[1], and Le Xie[1,3,*]

[1]Department of Electrical and Computer Engineering, Texas A&M University, College Station, Texas, USA
[2]Breakthrough Energy Sciences, Seattle, Washington, USA
[3]Texas A&M Energy Institute, College Station, Texas, USA
[*]Corresponding author: le.xie@tamu.edu
[†]Co-first author

ABSTRACT

Unprecedented winter storms that hit across Texas in February 2021 have caused at least 4.5 million customers to experience load shedding due to the wide-ranging generation capacity outage and record-breaking electricity demand. While much remains to be investigated on what, how, and why such wide-spread power outages occurred across Texas, it is imperative for the broader research community to develop insights based on a coherent electric grid model and data set. In this paper, we collaboratively release an open-source large-scale baseline model that is synthetic but nevertheless provides a realistic representation of the actual energy grid, accompanied by open-source cross-domain data sets. Leveraging the synthetic grid model, we reproduce the blackout event and critically assess several corrective measures that could have mitigated the blackout under such extreme weather conditions. We uncover the regional disparity of load shedding. The analysis also quantifies the sensitivity of several corrective measures with respect to mitigating the power outage, as measured in energy not served (ENS). This approach and methodology are generalizable for other regions experiencing significant energy portfolio transitions.

Main

The extreme winter storm and associated electricity outages in February 2021 are estimated to have caused more than 70 deaths[1] and $200 billion economic loss[2] in the state of Texas. Besides the official brief review[3] and ongoing internal investigation on the Electric Reliability Council of Texas (ERCOT), there have been preliminary reports from non-peer-reviewed articles[4–6] and press interviews[7,8] on potential causes and technical solutions for this blackout event. Given the complexity and confidentiality of the actual electric grid model and relevant information, it becomes very challenging for the broader research community to develop analysis and provide credible insights on such major events.

While researchers recently have contributed to the creation of large-scale synthetic grid models[9] for analysis such as macro-scope energy portfolio transition[10,11], cross-domain and open-source approaches to reproduce the Texas blackout event and quantify impact from corrective measures against extreme frigid weather are still at a nascent stage, with several gaps in existing research. First, existing open-source large-scale synthetic grid models are not ready-to-use for the event reproduction without rigorous calibration. Second, the lack of aggregated and processed event timeline data prevents exhaustive simulation and further investigation. Last but not least, the lack of consistent quantified criteria renders studies on the effectiveness of potential corrective measures and their combined effect incomparable.

Here, we collaboratively develop an open-source large-scale synthetic baseline grid[12], providing a realistic representation of the actual ERCOT electric grid, accompanied by the open-source data set along the event timeline. This ready-to-use multi-platform synthetic grid model is calibrated based on open-source data sets, including generation by source, load by weather zones, generation unit outage timeline, load shedding record, etc. To the best of our knowledge, it is the first fully open-source approach to model, simulate, benchmark, as well as propose corrective measures against the 2021 Texas power outage. The reproduction results transparently replay the timeline of the change of system generation capacity, load demand and load shedding associated with the key events, aiding public researchers in combing the event development process, investigating the event causes, and providing possible technical solutions. Additionally, we propose and evaluate multiple technical solutions that can possibly mitigate the electricity scarcity under such extreme weather conditions, including energy system winterization, interconnected HVDC lines, up-scaled demand response program and strategic energy storage facilities. Leveraging the synthetic grid, we perform quantitative analysis on the corrective measures in the aspect of reducing the extent of blackout events. Our results indicate the strong disparity among the winterization effectiveness for generation units of various source types and geographical regions, the quantitative assessment of certain corrective portfolios, and the interdependence of per-unit performance of corrective measures.

Open-source Synthetic Grid Model and Data

We first collaboratively develop an open-source, large-scale, synthetic baseline grid that provides a realistic representation of the actual ERCOT electric grid, and then integrate generation and load-related data along the event timeline, which are both publicly available on Github[12]. The original sources are detailed in the documentations in the Github repository (see Data and Code Availability). In this paper, the synthetic model creation particularly focuses on feasibility of the direct current optimal power flow (DCOPF) solution without transient stability assessment for the following reasons. First, DCOPF is commonly used for generation dispatch in the real-world system operation under normal conditions, due to its computation efficiency compared to the alternating current optimal power flow (ACOPF). Second, although maintaining the system transient stability affects the system operation under emergency conditions, the major decisions that determine the blackout event thread, such as generation dispatch and load shedding, mostly depend on the power flow solution feasibility. Finally, regulations on critical energy/electric infrastructure information (CEII) limit the disclosure of information about actual power grid components, and hence dynamic model parameter calibration for generators is impractical due to the lack of publicly available information.

For the purpose of blackout event reproduction and 'what-if' analysis, we create a comprehensive blackout event dataset via collection from publicly available sources[3,13–16] and estimation (see Methods). This dataset integrates actual load by weather zone, actual generation by source, 7-day-ahead load forecast by source, solar and wind generation forecast, generation units outage, actual available generation capacity, actual load shedding and customer power outage into a single ready-to-use format. Here, we define the ***counterfactual load*** as the 7-day-ahead load forecast and the simulated ***load shedding*** as the gap between the post-shed and counterfactual load, and introduce the ***estimated generation capacity*** by weather zone based on rated generation capacity, thermal generation units outage and actual renewable generation (see Methods), all of which play important roles in the event reproduction and what-if analysis.

The synthetic ERCOT grid model is adapted from an existing test system[17] and rigorously calibrated in several aspects, namely generator units capacity, and transmission line rating (see Methods). The geographical load distribution comes from the existing grid model[9], while their real-time magnitudes in simulation are adjusted according to the real load dataset or calculated ones depending on whether the real load data are available. The generator units capacities are updated to the actual available generation capacity[15] in January 2021. Without modifying the network topology, some transmission lines are upgraded to ensure that the model remains feasible in the period leading up to the blackouts and that no renewable generators are unreasonably curtailed due to congestion.

Integrating the open-source datasets, the ready-to-use multi-platform synthetic grid model is the first open-source simulation package dedicated to potentially provide firm interdisciplinary insights into the particular real-world blackout event. To give an intuitive impression on the blackout event, we provide an event overview along with regional generation outages and customer power outages (Fig. 1). The timeline of the whole blackout event (Fig. 1-a) that contains the actual total load, actual and estimated generation capacity shows the electricity scarcity due to the high load demand and wide-ranging generation outage. The actual generation and generation outage across eight ERCOT weather zones (Fig. 1-b) show that the generation outage at the darkest hour mainly consists of natural gas thermal generation outages across ERCOT and renewable generation outages in the North, West, Far West and South zones. We also find the regional disparity of load shedding (Fig. 1-c) from the aggregated county-level utility-reported customer outage data[16] during the "darkest" period, namely from 8 p.m. February 15 to 11 a.m. February 16. Specifically, the satellite counties around Houston in the Coast zone and several counties distributed in the West zone suffered the most severe outages. We notice the significant gap between the estimated generation capacity and actual online capacity before February 15 and increasing mismatch between them after noon on February 16 that are in line with expectations due to several reasons explained in Supplementary Note 1. We have observed that there exists a substantial mismatch between actual load and either actual online or estimated generation capacity, which is beyond the reserve limit. This mismatch may be attributed to multiple reasons, such as transient stability requirements, reactive power demands, and capped wholesale market price[18], which deserve more investigation but are nevertheless outside the scope of this paper. To show the complex but realistic features of the synthetic grid, we visualize the topology of the whole synthetic grid (Fig. 2), of which load distribution, generation units capacity and transmission lines rating are calibrated based on the static ERCOT grid-related data (see Methods). In the following analysis, we will leverage the synthetic model along with the blackout event dataset to reproduce the blackout event via simulation and perform quantitative assessments of multiple corrective measures against extreme frigid weather.

Reproduction of the 2021 ERCOT Blackout Event

To reproduce the ERCOT blackout event from February 15 to February 18, we simulate the synthetic grid model using the aggregated data, where realistic load shedding allocation and DCOPF are key steps. We take the ***estimated generation capacity*** (the binding constraint for load shedding) and ***counterfactual load*** (the ebb-flow pattern of load) as the simulation inputs. To achieve the fidelity of load shedding, we mimic the guides of load shedding and restoration[19,20] to determine the total load shedding amount at any given moment, and perform appropriate spatial allocation of load shedding to reflect its regional disparity (see Methods). We reproduce the blackout event by iteratively solving DCOPF given the post-shedding load (see Methods), which reveals the hourly change of geographically distributed load, generation and load shedding across the ERCOT in detail.

We demonstrate the fidelity of the synthetic grid and the associated simulation methods by the reproduction results of load shedding and generation composition (Fig. 3). To quantify the severity of the blackout event, we use the power system reliability index ***energy-not-served***[21] (ENS), defined as the integral of load shedding over the event timeline, to quantitatively evaluate the load shedding throughout the rest of this paper. We first demonstrate the fidelity of the geographical load distribution and the designed load shedding algorithm by the good match between the actual and simulated total load shedding (Fig. 3-a) that respectively represent a total of 998.8 GWh and 929.6 GWh ENS. The unavoidable mismatch attributes to the combined effects of errors in synthetic grid modelling and system operation under emergency conditions (see Supplementary Note 2 for the remark on the mismatch). We then validate that the simulation well captures the regional disparity of load shedding across eight weather zones[22] by comparing the simulated zone-level normalized load shedding with the real one (Fig. 3-b). It shows that Far West experienced the most disproportional load shedding among all zones and Coast has suffered from a significantly worse condition compared to the other two most populous zones: North Central and South Central. Finally, we validate the fidelity of generation units capacity by type and generation cost curves used for DCOPF by showing the almost perfect match between actual and simulated generation composition throughout the event (Fig. 3-c). The reproduction results validate the synthetic baseline model, the related data and the associated simulation methods, which provide a reliable basis for the following what-if analysis. Additionally, the reproduction results can transparently show the change of load, generation and load shedding along the timeline, aiding public multidisciplinary researchers in combing the event development process, investigating the event causes and providing possible technical solutions. The transparency and reproducibility of the synthetic grid model also allow public researchers to contribute to further model development and calibration.

Quantitative Assessment of Corrective Measures against Extreme Frigid Weather

In order to provide firm insights into potential solutions against problems revealed by extreme frigid weather, we start from investigating four possible corrective measures, namely, generation units winterization, interconnection HVDC lines, up-scaled demand response program, and strategic energy storage facility (see Supplementary Figure 2 for conceptual diagram). Generation units winterization only refers to the adapted winterization treatments for electric energy generation units, assuming no winterization is currently applied for any units. Particularly, we reserve the impacts of wide-ranging natural gas scarcity[6] due to failures in the non-winterized natural gas supply chain (see Methods and Supplementary Note 4). Additional HVDC interconnections, besides two existing HVDC ties, respectively connect from the Western Interconnection to the West zone and from the Eastern Interconnection to the Coast zone, require necessary transmission lines upgrade around the locations of their converter stations (see Methods). Up-scaled demand response refers to various incentive programs distributed across ERCOT that require voluntary reduction of electric energy demand. Energy storage refers to the large utility scale storage facilities that absorb the excessive energy during off-peak hours and release it at high power during emergency hours. Here we treat the energy storage as the first-aid measure while taking the other three as the sustained electricity supply measure, especially viewing the generation units winterization as the primary preventive measure. Therefore, we conduct quantitative assessment of all corrective measures from different perspectives in the following analysis.

Taking these corrective measure settings into account, we first quantify the impacts of each single sustained electricity supply measure of distinct extents in load shedding (Fig. 4). We find that 60% generation units winterization can effectively reduce the ENS from 929.6 GWh to 40.8 GWh (Fig. 4-a), and about 80% generation units winterization can prevent the blackout entirely, where we reserve the impacts of non-winterized natural gas supply chain. We also find that HVDC lines and up-scaled demand response of equal capacity have similar but different effectiveness on mitigating the electricity scarcity (Fig. 4-b,c), which respectively reduces the ENS by 64.1 GWh and 67.5 GWh per 1 GW capacity (see Supplementary Note 6 for more details). Since energy system winterization is the most straightforward solution against extreme frigid weather, we attach additional importance to prioritizing the winterization of generation units of specific source types in different regions. We perform the quantitative assessment of the effectiveness of facility winterization by source and region on the electricity scarcity mitigation. The results indicate the distinct performance of per-GW generation units winterization (see Supplementary Note 7 for more details). Based on this, we suggest the priority of winterization for the disabled nuclear generation units located in the

South Central, natural gas generation units across ERCOT, coal generation units in the Coast and wind generation units in the West.

Given the quantitative assessment of single sustained electricity supply measure, we investigate the performance of several sustained electricity supply portfolios and assess the first-aid capability of energy storage on the basis of sustained sources. We have selected three appropriate winterization portfolios based on the foregoing priority analysis (see Supplementary Table 1) to provide a quantitative assessment in terms of additional ENS reduction contributed by both HVDC and demand response (Fig. 5). First, we find that the performance of HVDC and demand response are slightly different but almost equivalent under certain cases of winterization portfolio. Second, we find the per-GW performance of HVDC and demand response decreases as the winterization capacity increases. For first-aid outage mitigation at the load shedding peak hour, we focus on load shedding peak clipping by the strategic energy storage facilities on top of sustained corrective measure portfolios, each refers to one of the three winterization portfolios (see Supplementary Table 1) together with HVDC and demand response of 2 GW. We find that the performance of per-GWh capacity reduces as the total energy storage capacity increases, or along with increasingly sufficient sustained supply corrective measures (Fig. 6).

To summarize the key findings obtained in the foregoing quantitative analysis, we find the strong disparity of generation units winterization of various source types in multiple regions, and the interdependence of per-unit performance of corrective measures, based on the quantitative assessment of certain corrective portfolios.

Discussion

We introduced an open-source cross-domain synthetic ERCOT grid model associated with the blackout event-related data, which is the first-of-its-kind for broader energy researchers to provide insights into the 2021 Texas power outage event. Simulation results based on this open synthetic model are shown to have captured key characteristics of the real-world event, uncovering the key regional disparity of load shedding. The quantitative assessment of the corrective measures and portfolios has indicated the strong disparity of winterization effectiveness among generation units of various types in multiple regions and the interdependence of per-unit performance among corrective measures. It can immediately inform policy makers of the priority of generation units winterization, the quantitative assessment of certain portfolios on mitigating the blackout and the necessity of launching systematic investigations on the combined effects of corrective measures, which can potentially be generalized for other regions around the world which are experiencing the dual challenge of energy portfolio transition and extreme weather conditions.

This open-source, cross-domain, data-driven approach to analyzing a real-world power grid during extreme events provides a fresh perspective to allow broader climate and energy research communities to have high fidelity characterization of what exactly happened and what could have been corrected in a large power system, as nations and regions aggressively tackle energy and climate challenges. The transparency and reproducibility of the synthetic grid model will contribute its unique value to the future energy policy making and technological solution discussion in the broader context of energy portfolio transition and frequent extreme climate, which otherwise are mostly closed-door research in a few government agencies and transmission organizations on confidential real-world models.

For the future public research and internal ERCOT investigation, it will be fruitful to provide solid and reasonable explanations to the following observations that are unanswered in this paper. First, we notice the wide-ranging natural gas generation capacity outage and de-rating are not simply due to the freezing temperature, but also to natural gas scarcity and interruption in the supply chain. It is particularly important to estimate and predict the impacts of interdependence between two energy infrastructure systems on the overall energy system reliability and energy market stability on both sides under extreme weather conditions. Second, we notice the price-ceiling-hitting whole-sale electricity price[18] at $9,000 per MW, that lasted for three days ending on February 18. Its quantified impacts on generation dispatch and load restoration still remain unknown. More investigation is necessary for demonstrating and developing a benign power market mechanism that can encourage improving the reliability and resiliency of power grids. Last but not least, the interdependence of per-unit performance among corrective measures emphasizes the necessity of systemic assessment on the combined cost-effectiveness of technical solution bundles.

Methods

Data Aggregation

In order to reproduce the blackout event and perform quantitative what-if analysis, we integrate the blackout related data during the event period between February 14 to February 18. The original sources for all datasets are provided in the Data and Code Availability section. We integrate the datasets via two ways, namely data collection from multiple resources[13–16] and data estimation.

- *Data Collection*: We collect actual load, actual generation, 7-day-ahead load forecast and 7-day-ahead solar generation forecast data from the ERCOT regular data channel[13]. We collect generation units outage data from the source[14] dedicated for the blackout event, which specifies the outage period, outaged capacity, source type, and location of outaged and de-rated generator units. Note that only part of all generation outages are included in this source, since some resource entities do not provide ERCOT consent to disclose, and outages shorter than two hours may not be included. We obtain generation capacity data from the Energy Information Admission (EIA) generation inventory data source[15]. Additionally, we get the customer power outage data[16] from PowerOutage, which has city-level utility-reported number of customers suffering power outage.

- *Data Estimation*: We define the estimated generation capacity as the sum of total maximum online capacity of thermal and nuclear generation and total real-time varying available wind and solar generation capacity. Here the maximum online capacity of thermal and nuclear generation are equal to the seasonal maximum capacity[15] subtracted by the generation units outage[14], while the real-time varying capacity of wind and solar generation is the aforementioned collected wind and solar generation data[13]. We define the load shedding as the gap between the actual and counterfactual load data. Here the counterfactual load data refer to the 7-day-ahead load forecast. We also estimate the counterfactual wind generation as described in the literature[10] using the associated weather data[23] during the blackout event period. Wind generation estimation in this way can achieve the highest granularity. Due to the lack of weather data required by solar generation estimation model, the 7-day-ahead forecast solar generation is the alternative way for the counterfactual estimation. Great matches between actual and counterfactual wind and solar generation profiles before February 9 (see Supplementary Figure 1) demonstrates the accuracy of counterfactual generation, and it also indicates that the impacts of the winter storm on renewable generation approximately started from February 9.

Synthetic Grid Creation

The synthetic ERCOT grid model is adapted from the existing test system[17], and rigorously calibrated in several aspects, namely, system topology, geographical load distribution, generation units capacity and transmission lines rating. Note that although the latest released synthetic Texas 7,000-bus grid[24] offers more granularity in terms of buses and zones, the zones do not line up with the data available from ERCOT, rendering remarkable difficulty for model calibration. Therefore, we still choose this 2,000-bus case as the base model.

- *Load distribution*: The geographical load distribution comes from the original design of the synthetic grid model[9], of which the relative sizes are reasonably determined by the demographic and geographical information. The real-time sizes of loads in simulation are further adjusted to the real hourly load dataset or calculated counterfactual ones. As the public datasets only disclose aggregated load of each weather zone, all loads within each weather zone are proportionally scaled such that the sum of all loads in each area equals the published numbers.

- *Generation units capacity*: The existing test system contains generation capacity inventory up to 2016[9] plus the largest generators added in the period from 2017 to 2019, with the entire generator fleet scaled to match totals by type and zone at the start of 2020[17]. To update this dataset to 2021 conditions, we add eight new generators: two natural gas generators (a total of 427 MW), one biomass generator (100 MW), four solar generators (742 MW), and one wind generator (220 MW). These generators were added at high-voltage buses in the synthetic network closest to their real locations. Finally, the generation fleet was scaled such that totals by type and weather zone match the totals from EIA Form 860-M, December 2020 (to account for any uncaptured additions, retirements, de-ratings, etc.).

- *Transmission lines rating:* The topology of the system is adopted from the synthetic Texas 2,000-bus grid as described in the literature[9]. Without modifying the topology of the transmission network, their capacity ratings and imdepances are tuned to emulate transmission expansion to accommodate the additional generation resources, additional HVDC interconnections and 2021 demand. Transmission lines are upgraded as necessary to ensure network feasibility and to avoid unrealistic curtailment of variable renewable generators. Specifically, 59 out of 3,206 branches are upgraded, representing 108.4 GW-miles of transmission lines upgrades (out of a total of 19,374 GW-miles in the base grid. These transmission upgrades are mostly in the Far West (29) and North (14) weather zones, where growth of demand and generation resources has been greatest relative to the 2016 transmission network capacities.

Simulation based on Synthetic Grid Model

Load Shedding and Restoration Operation Principles

In ERCOT operation protocols, when the system-wide reserve drops to a dangerous level that qualifies for Energy Emergency Alert (EEA) conditions, the grid operator will use different resources from various participants of the ERCOT market to maintain grid security. In EEA levels 1 and 2, ERCOT will first contact industrial loads that agreed to be disconnected during emergencies and call upon available demand response programs. In EEA level 3 events during which the operating reserve capacity is below 1000 MW, ERCOT will ask transmission companies to shed load, typically done through rotating outages. In our simulations, we aim to follow a similar process in determining the total amount of load to shed while maintaining simplicity and generality. For each snapshot, we start by applying the counterfactual load and try to find a feasible power flow solution. If the available capacity cannot satisfy the full demand or the supply is limited by transmission line congestion, DCOPF will be infeasible. In that case, we then gradually reduce the load across the network until a feasible solution is found. Similarly, if the system-wide reserve is high enough and there is active load shedding from the past hours, we attempt to slowly reconnect them back until the operation reserve has been depleted. The full logic flow of load shed in simulation is listed in Algorithm 1.

Algorithm 1: Iterative Load Shedding in Simulation

```
Load renewable generation profile of hour t, P_g^t into model
Modify thermal generator capacity based on unit outage data
Load counterfactual load of hour t, P_l^t into model
Apply load shedding from the past hour P_ls^{t-1} to load buses
Compute system-wide capacity reserve P_r^t = Σ_i (P_{g,i}^t − P_{l,i}^t) + P_ls^{t-1} ∀i ∈ [list of all buses]
Attempt to solve DCOPF on the base profile
if DCOPF is infeasible or P_r^t < P_{r,min} then
    while DCOPF is infeasible or P_r^t < P_{r,min} do
        Increase load shedding: P_ls^t = P_ls^t + ΔP_ls
        Update P_r^t = P_r^t + ΔP_ls
    end while
else if Operation reserve P_r^t > P_{r,min} and P_ls^t > 0 then
    while OPF is feasible and P_r^t > P_{r,min} and P_ls^t > 0 do
        Decrease load shedding: P_ls^t = P_ls^t − ΔP_ls
        Update P_r^t = P_r^t − ΔP_ls
    end while
end if
Save P_ls^t as the minimum load shedding for hour t
```

Details of Blackout Event Reproduction

- *Load and Load Forecast Profile*: In the reproduction of the outage event, we apply the real historic load during the period between February 12 and February 18 to the synthetic Texas network. The ERCOT load data are divided into eight weather zones in Texas, each containing a specific set of counties. In the simulation, we scale the base value of every load bus within each weather zone such that the total load capacity in the zone equals the ERCOT load forecast data on the same hour, which is used as the counterfactual load profile.

- *Renewable Generator Capacity*: We have estimated the unit-level wind and solar capacity data during the event periods using the combination of available weather data and ERCOT generation-mix data. In the reproduction of the outage event, the unit-level data are all scaled according to the total actual renewable generation data published on EIA[15]. These data are set to be the maximum real power output for renewable generators and is subject to further curtailments, should congestion in the lines occur. The renewable generators are set to have zero cost in the DCOPF formulation to prioritize them over thermal energy sources.

- *Dispatch-able Generator Capacity*: We use the ERCOT unit-level outage report[14] to determine the maximum real power output capacity for thermal generators. Although the maximum rate capacity for thermal plants is fixed through the event, many thermal generators have experienced outage or de-rating due to various reasons, including limited fuel supply, facility freezing and planned maintenance. As the generators in the synthetic networks are equivalent generators, exacting matching with the outage report is not possible. Instead, the outage data are first aggregated to county-level and used to set the maximum capacity of all thermal generators of the same fuel type in each county.

- *Formulation of DCOPF*: Using deterministic system demand and renewable generation data, the actual output of dispatchable generators (coal, natural gas and nuclear) and the power flow pattern in the network is determined by Direct-Current Optimal Power Flow (DCOPF). DCOPF is an optimization formulation that computes the most economic real power output assignment for all dispatch-able generators in a network, such that all transmission line flow is below their thermal limit and the total real power generation equals the total demand across the network. The Matlab package

Matpower is used to solve DCOPF for all simulations. A detailed description and formulation of DCOPF implemented by Matpower can be found in their documentation[25].

- *Cost Curve*: The cost curves of generators in the original synthetic network[9] are revised to make an even closer match with reality. We have run a year-round multi-period DCOPF simulation using 2016 ERCOT renewable and load profile data to confirm that the total generation from each of the fuel sources is sufficiently closely matching historical data. A detailed experiment procedure and result comparison can be found in the literature[10].

Generator Outage and Corrective Measure Modelling

To quantitatively assess the impact of generator outage on the severity of the outage event and evaluate the effectiveness of potential corrective measures such as the additional HVDC interconnections, generation units weatherization, up-scaled demand response programs and energy storage, it is necessary to model each of these elements appropriately in our synthetic grid. The detailed modelling method is documented below:

- *Generator Outage*: The unit-level generator outage data is retrieved from the ERCOT public report[14,26]. As detailed generator information is not available to the public (especially for natural gas, wind and solar generators), we have 606 equivalent generators across the network such that the area-wide aggregated generation capacity and profile can match real ERCOT records. To match the real outage data with synthetic equivalent generator, we pre-process the data by aggregating the total outage capacity for each county and fuel type. The county-level outage data are used to scale the maximum real power output of all corresponding generators in the same county and of the same fuel type in the synthetic network.

- *Generator Weatherization*: Weatherization is a preventive measure to reduce the impact of extreme weather conditions on the functionality of infrastructures. Different types of generators require different types of weatherization treatments: wind turbines require blade and gearbox heating while gas plants may need anti-frost treatment for facilities. Despite the potentially big difference in weatherization cost and complexity, our focus is more about evaluating the effectiveness of weatherization among different generator types and geographical regions. To this end, we only specify the amount of MW of weatherized generators for each fuel type in each weather zone and try to compare the effectiveness on the reduction of ENS as a result of weatherization. We have also considered the scarcity of natural gas supply before and during the winter storm by approximating the de-rating of the winterized generators caused by gas supply shortage, using disclosed unit de-rating data from ERCOT (see Supplementary Note 5). When computing the area-level available capacity during counterfactual simulation, we only apply weatherization to generators that were completely out, as the de-rating of the running generators was highly likely caused by lack of gas supply. The weatherized generators are also de-rated based on the extent of de-rating of running gas generators in the same county.

- *HVDC Ties*: We have included two existing HVDC ties to the Eastern Interconnection in our synthetic network model. These two existing conveter stations are modelled as fixed equivalent loads for DCOPF computation. In each hour, the real tie flow data from ERCOT is assigned as real power demand for the equivalent loads and the sign is determined by the direction of DC tie flow. This is meant to make the DC tie flow exactly the same as real data. For counterfactual studies, we have included two additional HVDC ties, one to the Western Interconnection and another to the Eastern Interconnection. We have adopted a commonly used design[27] in determining the location for the converter stations and upgrade the transmission lines around the converter stations (see Supplementary Method 1). As the additional HVDC ties are introduced to be counterfactual corrective measures to supply any extra power during the event, their actual output power needs to be adjusted according to the ERCOT system demand. Hence, the new DC ties are modelled differently as equivalent generators with a cost function representing the hypothetical cost to buy power from neighboring states. The magnitude and direction of their tie flow is determined by OPF result.

- *Demand Response*: Demand response refers to various incentive programs that encourage voluntary reduction of electric energy demand during peak or emergency hours. Although most demand response programs in ERCOT are still in development at the current stage and mostly target large industrial, commercial or aggregated customers, it has the potential to scale up quickly and provide a valuable demand side resource during similar energy emergencies. In our simulation, the effect of a demand response program is modelled as a form of voluntary load reduction with prior agreement between load serving entities and customers which does not count to ENS. During energy emergencies, load resources from demand response programs are the first to be committed before all of the other more costly steps. Hence, we also prioritize available demand response capacity over storage and forced load shedding. When the system reserve is below 2300 MW which corresponds to ERCOT EEA level 1, the loads across the synthetic network are reduced up to the maximum allowed demand response capacity.

- *Energy Storage*: The purpose of energy storage is to absorb excessive energy from renewable sources during off-peak hours and release stored energy during peak and emergency hours. Unlike other types of corrective measures that are more suitable in reducing the overall severity of the outage by providing sustained additional power supply, the advantage of energy storage lies in its ability to provide relatively large power output during a short period, which can be used to bridge through "most difficult" hours. To emphasize this, we assume all storage capacities are fully charged prior to the event and commit them during the hours when the level of forced load shed is around the highest. The contribution of energy storage is reflected in the reduction of peak load shed capacity.

Data and Code Availability

The open-source synthetic ERCOT model and the corresponding dataset used for blackout event reproduction and quantified what-if analysis are publicly available on Github[12]. A tutorial and examples for running the code using provided dataset are also available in the Github repository.

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Figures & Tables

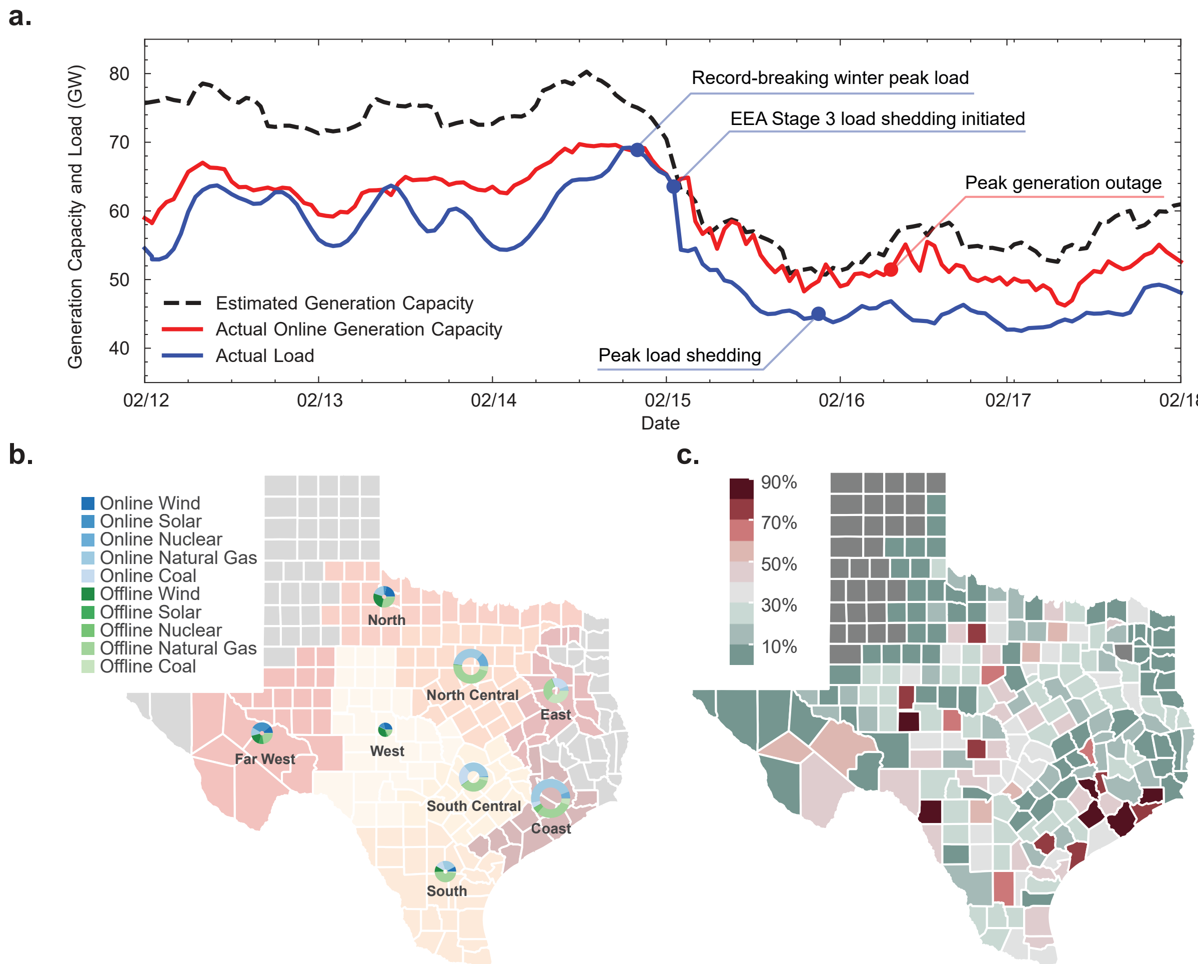


Figure 1. Overview of the 2021 ERCOT blackout event from the perspective of generation capacity and load shedding. a, Blackout event overview in terms of generation capacity and actual load associated with the key event labels. The significant gap between the estimated generation capacity and actual online capacity before February 15 and increasing mismatch between them after noon on February 16 are in line with expectations due to several reasons explained in Supplementary Note 1. **b**, Online and offline generation capacity by source in ERCOT weather zones at 12:00 p.m. February 16. The ring size is determined by the zone-level total generation capacity and its color represents the type of generation capacity. The block color represents the weather zone where the county is located (grey blocks are not within eight weather zones). **c**, Normalized county-level customer outage percentage during the "darkest" period. The block color represents the county-level customer outage percentage[16], where the ERCOT average outage percentage is 31% (grey blocks mean no data available). The "darkest" period is ranging from 8 p.m. February 15 to 11 a.m. February 16, possessing the largest load shedding amount.

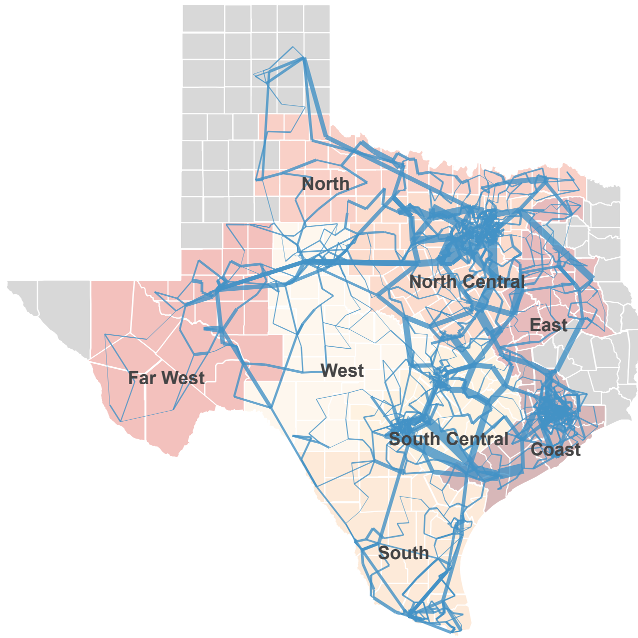


Figure 2. **Visualization of the large-scale synthetic ERCOT grid.** Here the branch width is proportional to the transmission line rating. This synthetic grid contains 606 generators, 1,350 loads and 3,206 branches, of which the generation units capacity, transmission line rating and load distribution are calibrated based on the available ERCOT grid-related data.

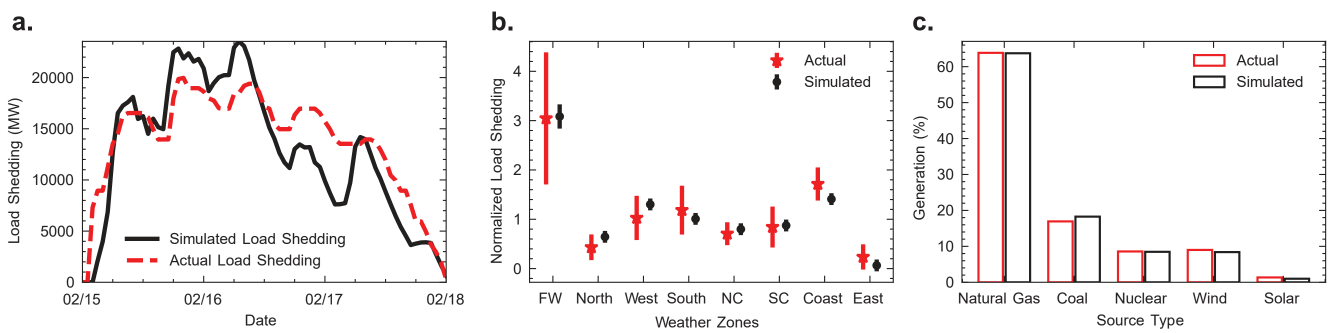


Figure 3. **Blackout event reproduction via simulation on the synthetic grid in comparison with the real data. a**, Comparison between the simulated and actual total load shedding curves. **b**, Zone-level normalized load shedding with 95% confidence interval (CI) during the period between 8 p.m. February 15 and 12 p.m. February 16 that has the highest load shedding. FW, NC and SC respectively represent Far West, North Central and South Central zones. Here the normalized load shedding refers to the ratio of load shedding percentage over online load percentage for each zone. We use the estimated load shedding data based on the counterfactual and actual load data from ERCOT rather than customer outage data[16] as the real benchmark (See Supplementary Note 3). **c**, Comparison between actual and simulated percentage of generation compositions of various source types throughout the event.

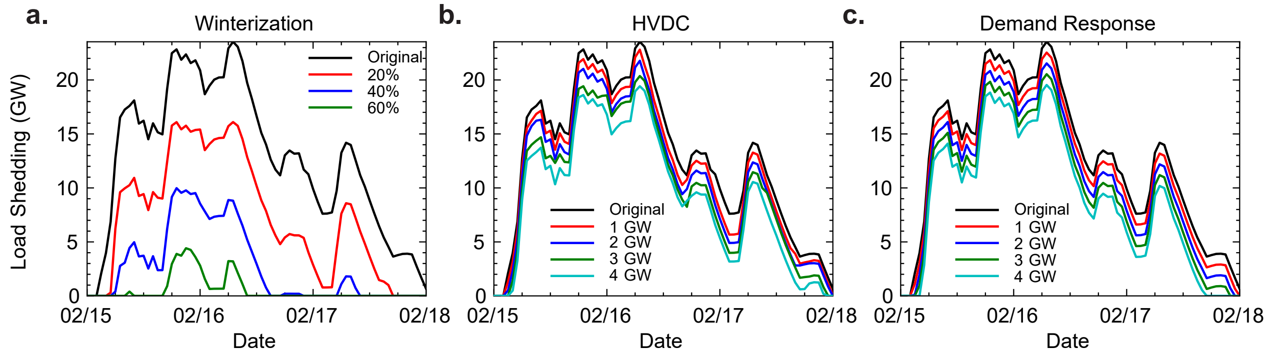


Figure 4. Quantitative assessment of each single sustained supply measure in terms of load shedding (GW). a, The impacts of additional facility winterization on load shedding with different percentages from 20% to 60%. These percentages correspond to the winterization for generation capacity of 21.7 GW, 43.4 GW and 65.1 GW. **b**, The impact of additional HVDC lines on load shedding with the capacity ranging from 1 to 4 GW. **c**, The impact of up-scaled demand response program on load shedding with the capacity ranging from 1 to 4 GW. Note that winterized generator units and demand response programs are deployed across ERCOT without priority in any specific area. Here the original curve refers to the load shedding in the event reproduction with no corrective measures.

Source Type	Far West	West	North	East	Coast	North Central	South Central	South
Nuclear	—	—	—	—	—	—	38,205	—
Natural Gas	37,058	12,338	18,993	16,908	25,129	29,236	18,905	23,279
Coal	—	—	—	266	18,719	1,967	266	5,768
Wind	6,865	15,178	4,479	5,188	795	—	—	—

Table 1. Quantitative assessment of generation units winterization by source and region in terms of ENS reduction (MWh). Each entry in the table shows the resulting reduction of ENS (in MWh) for 1 GW generation capacity winterization of each source type in each weather zone. A crossed-out entry means that the lack of associated generation outage data renders the evaluation of this certain winterization non-applicable.

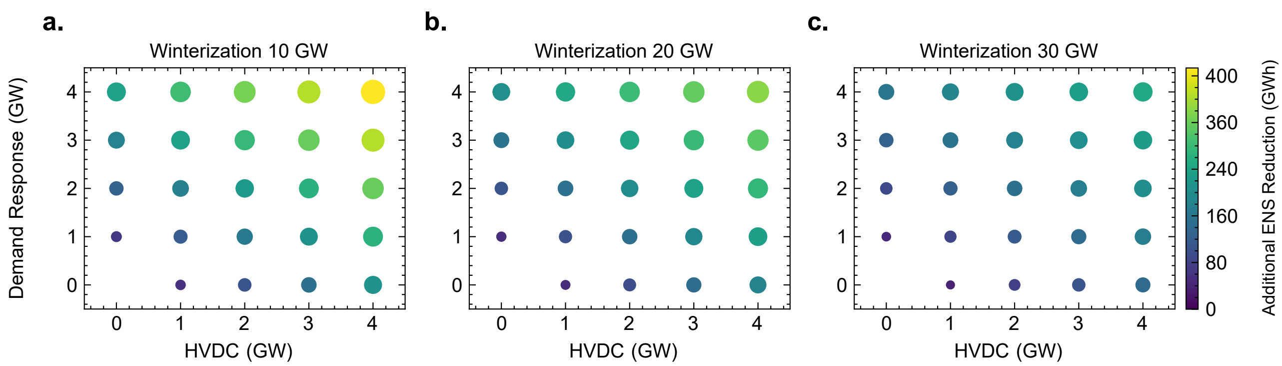


Figure 5. Additional ENS reduction (GWh) by HVDC and demand response given different winterization portfolios. a, b, c, respectively show the additional ENS reduction contributed by HVDC and demand response that is represented by both bubble size and color, given different total winterized generation capacity. Here the winterization portfolios in three cases are determined based on the results in Table 1 (see Supplementary Table 1 for more details). The ENS reduction contributed by winterization portfolio alone are respectively 266.2 GWh, 467.0 GWh and 628.9 GWh for the case of 10 GW, 20 GW and 30 GW winterized capacity.

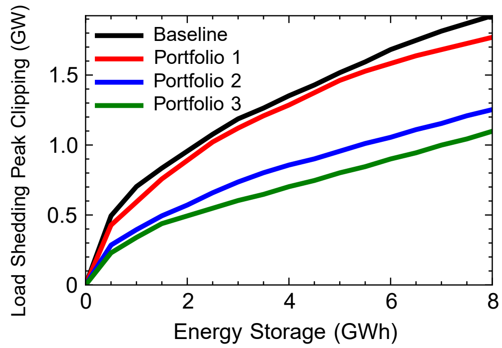
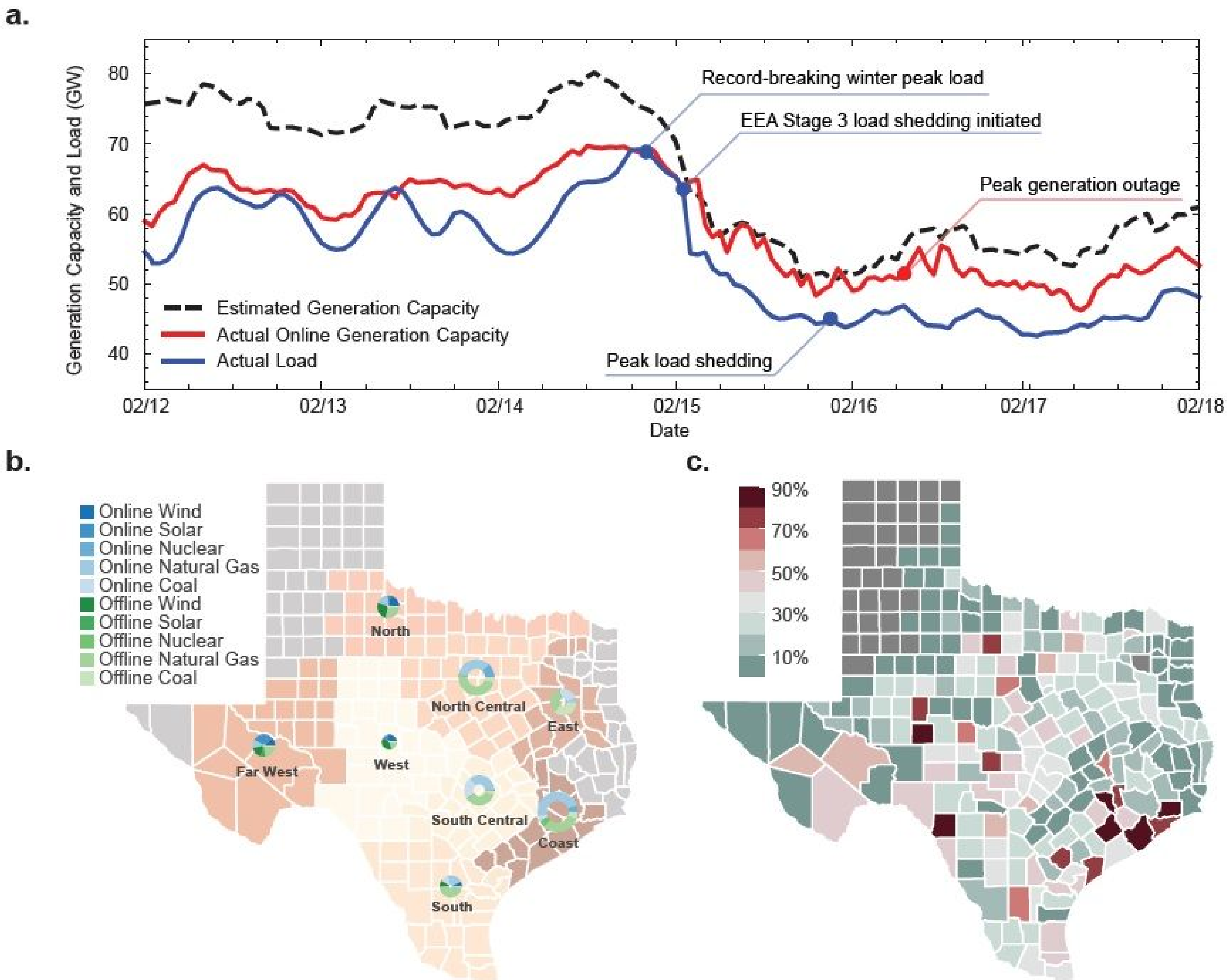


Figure 6. Load shedding peak clipping of energy storage facility. The baseline refers to the model without other corrective measures, while the portfolio 1, 2 and 3 respectively consist of one of three winterization portfolios in Supplementary Table 1 together with HVDC and demand response of 2 GW capacity.

Figures



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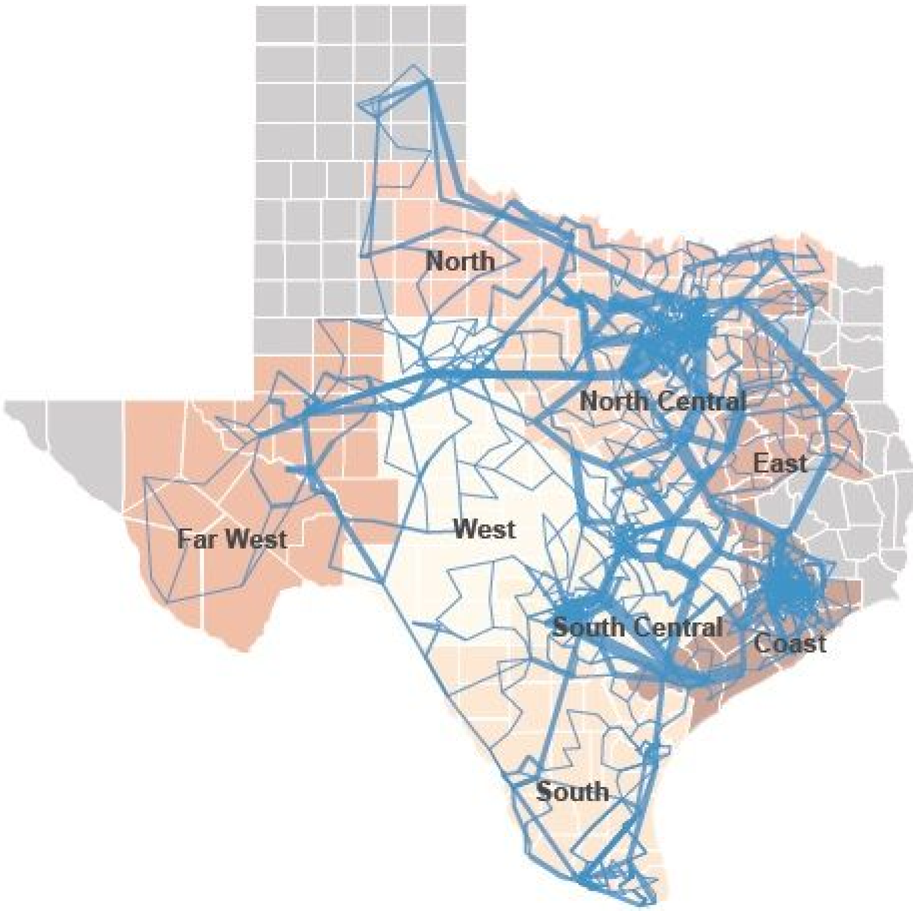

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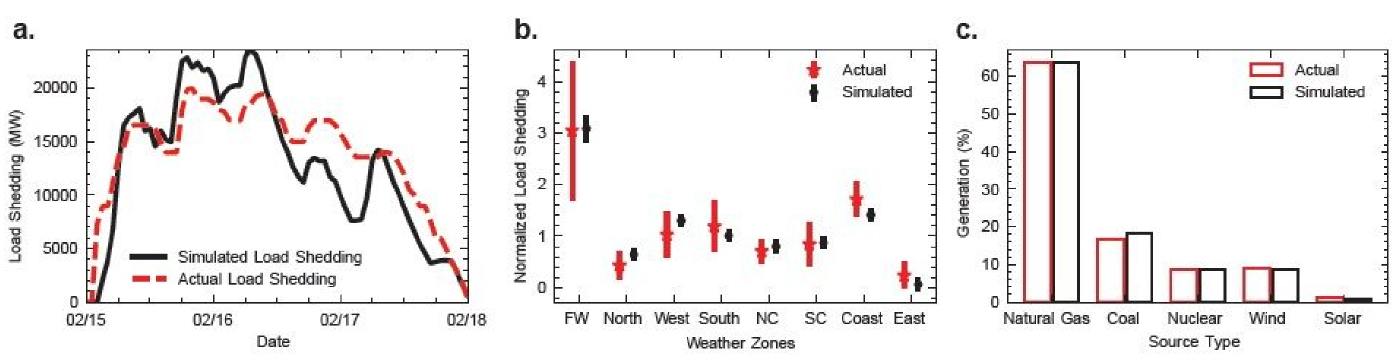

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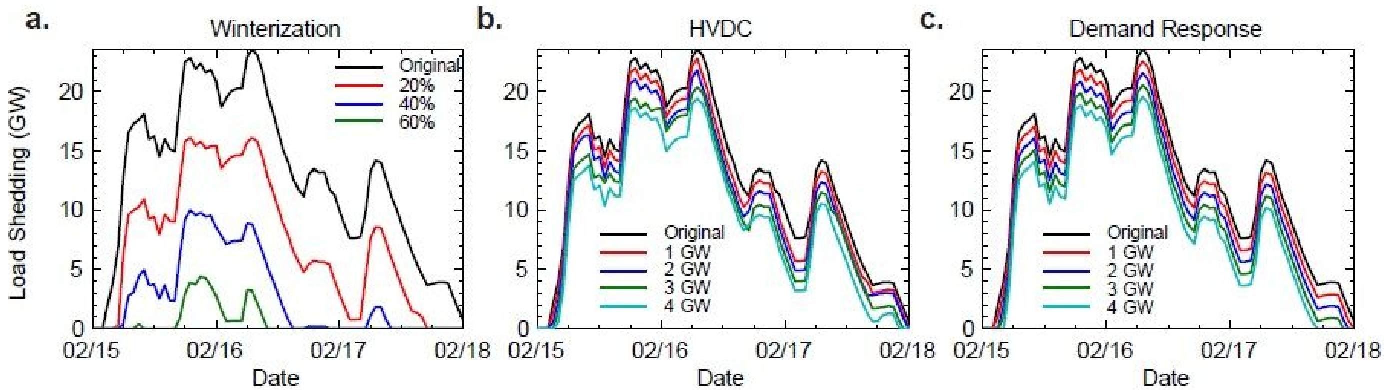

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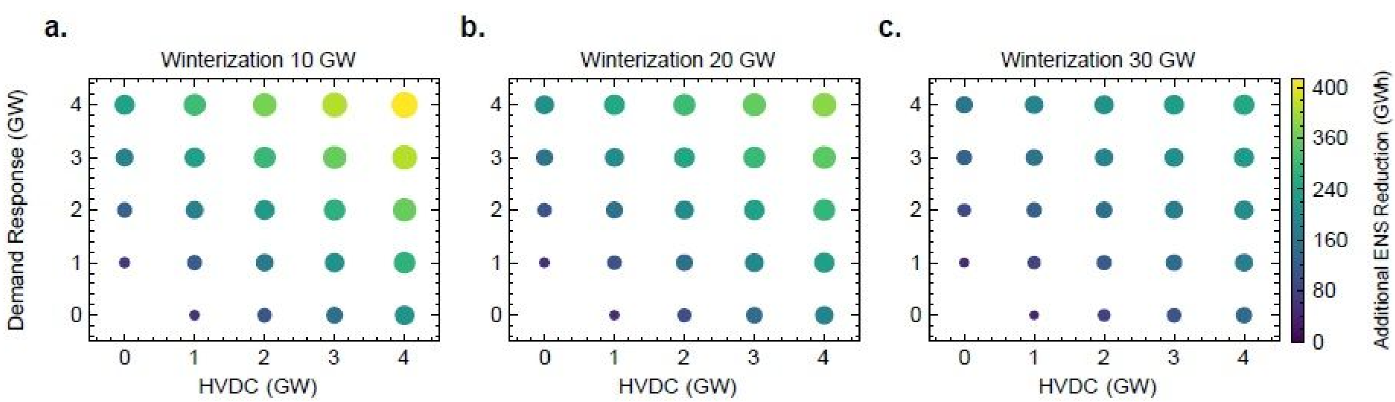

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Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ERCOTOutageSupplementaryNatureEnergy.pdf