Profitability and investment risk of Texan power system winterization

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September 2021

Abstract

A lack of winterization of power system infrastructure resulted in significant rolling blackouts in Texas in 2021. We therefore assess if incentives for winterization on the energy only market have been sufficient, combining power demand estimates with estimates of power plant outages to derive power deficits and scarcity prices. The loss of load in 2021 was the most severe in our simulation of 71 years. Expected profits from winterization of a large share of existing capacity are positive. However, investment risk is high due to the low frequency of freeze events, potentially explaining under-investment, as do high discount rates and uncertainty about power generation failure under cold temperatures. As the social cost of power deficits is one to two orders of magnitude higher than winterization cost, regulatory enforcement of winterization is welfare enhancing. Current legislation can be improved by emphasizing winterization of gas power plants and infrastructure.

Keywords— Texas, extreme event, power systems, winterization

Weather extremes such as storms can significantly affect the reliability of power systems [1]. The increasing use of variable renewable energies additionally exposes power systems to hazards caused by weather extremes [2, 3]. However, recently a gas power dominated system was deeply impaired by a weather extreme: a cold spell over Texas, between February 10^{th} and February 20^{th}, 2021 with temperatures far below 0°C caused a failure of large parts of the Texan power system. The combination of extraordinarily high winter electricity demand and more importantly the failure of significant power generation capacities, both due to low temperatures, resulted in up to 4.5 millions of Texans being cut-off from their electricity supply [4].

A first retrospective analysis of the event by Busby et al. [5] discusses the magnitude of the event and its causes, indicating that the total economic loss amounted to 130bn$ and that the outage of gas power plants was mainly responsible for the high deficits in power generation capacity. Wu et al. [6] provide a power grid simulation to conduct a very detailed analysis of the 2021 event and, Doss-Gollin et al. [7] have shown that lower temperatures than in February 2021 have been observed in the past 71 years, and heating demand predicted from temperature data would also have been higher in the past, although the 2021 freeze event was comparably long. These previous studies indicate that there is a striking gap between the occurrence probability of such an event, its large scale economic and social cost, and the lack in winterization efforts. However, none of these studies assessed whether the economic incentives for power companies to invest into winterization have been high enough, when the 2021 event is put into a long-term climatic context.

As winterization was not strongly enforced by regulation in Texas, power generators had to rely on the incentives provided by the energy only market to arrive at investment decisions. These incentives consist mainly of regulated price spikes at the spot market when generation capacity is scarce [8]. Hence, we assess here how revenues from winterization compare to its cost for power companies. Technically, we combine estimates of temperature dependent load with a model of power plant outages, taking into account 71 years (1950–2021) of past climate from reanalysis data. Climate change, of course, may have an impact on temperatures. We therefore also assess if trends in the occurrence of extremely cold temperatures and loss of load events can be observed. Furthermore we conduct an extensive sensitivity analysis to show uncertainties arising from our modelling choices. To put the event into context, we first discuss details of the relationship of temperatures, electricity load, and power plant failures during the 2021 event. Subsequently, we analyze the long-term frequency of such events. Finally, we determine revenues from and costs of winterization and discuss potential reasons for underinvestment.

The 2021 event in a long-term climatic context

Starting on 10^{th} of February 2021, temperatures in Texas began to fall, causing load to increase from around 40 GW to over 70 GW by February 14^{th}–15^{th}. On February 15^{th} the freeze reached a critical level where substantial shares of generation capacities began to fail. Available capacities dropped below demand leading to a sustained power generation capacity deficit (Figure 1). Consequently, rolling blackouts had to be implemented to stabilize the grid and scarcity prices at the power market increased to the upper limit of 9000$/MWh. The deficit event continued until 19^{th} of February when rising temperatures allowed the system to recover.

The highest predicted demand in the February 2021 event was well above the highest load observed in winter in the period 2004–2020[1]. Our estimate is in the range of observed extreme summer loads (see Figure A.1). Our predicted demand matches ERCOT forecasts of peak load during the cold spell well - ERCOT forecasts were only about 0.26GW lower compared to our estimates[6].

Besides leading to high electricity demand, the low temperatures also caused substantial outages of generation capacities. Gas capacity failures were responsible for the largest share in power outages. As a result, loss of load occurred in 106 hours. Based on the predicted demand and the observed load, we estimate that in total 1.45TWh of

[1]The values of loss of load, capacity failures, and demand prediction in this section rely on our simulation and may therefore differ from ERCOT reports to some extent. As we focus on estimating the long-term frequency of such events, we did not aim at reproducing the February 2021 event in highest detail.

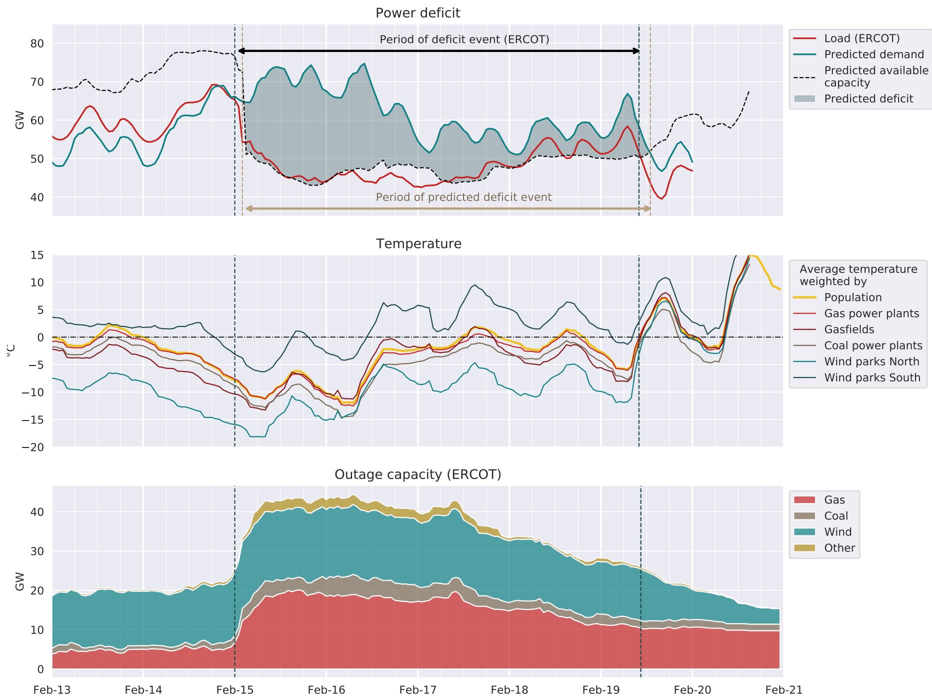

Figure 1: **The February 2021 event in retrospect** Observed load, predicted demand, available capacity, temperatures and capacity outages during the February 2021 event

load were affected by blackouts. Busby et al. [5] estimate the social costs of the power outages to amount to 130bn$. Therefore, the deficit cost around 87,000$/MWh, one magnitude higher than the current Value of Lost Load (VOLL) used by the Texan market regulator ERCOT, i.e. 9000$/MWh.

Outages of gas generation capacities started to increase rapidly at a gas power plant weighted temperature of -8.8°C, which is a record low temperature in the past 17 years (see Figure A.2). The outages were not only related to freezing of power plants, but also of gas supply infrastructure, including gas production equipment at gas fields. Power plants started failing rapidly when temperature weighted by gas fields dropped below -10.9°C. In the period 2004–2021, when no other outage events comparable to the one in 2021 was observed, this is a record low gas field weighted temperature (see Figure A.2). Therefore, gas supply infrastructure played an important role in the outage events. This is confirmed by ERCOT, which classified around 8GW of outages being related to limited fuel supply [9].

Coal generation capacity came offline at average temperatures weighted by coal plant locations of below -10.2°C. This temperature is at the very lower end of observed temperatures in the period 2004–2020. For both technologies, coal and gas, recovery time was substantial. Even when temperatures recovered back to over 0°C, according to ERCOT 11.3GW of thermal power plants, i.e. 18% of total available thermal capacity, stayed offline for another 16 hours.

Temperatures weighted by wind power plant locations indicate that the failure of wind power plants may be a more frequent event. While at the time of failure temperatures at wind parks in Southern Texas were at the very lower end of the temperature range observed in the period 2004–2020, the average wind park temperature in Northern Texas when wind power plants started to fail was just below 0°C and well within the range of previously observed low temperatures. Later on, temperatures reached record lows though at wind power plant sites. Compared to thermal power generation, wind power capacities began to fail much earlier and at higher temperatures. On February 13$^{\text{th}}$, when gas outages summed up to only 5GW, ERCOT already reports 13GW of wind capacity outages (Figure 1). This represented a loss of 3.3GW of wind power production on average at the prevailing wind conditions.

Our simulations of loss of load events using climate data from 71 years shows that the 2021 event was a record one. In total, we estimate that eight other severe power deficit events would have occurred in the current system assuming climate from the period 1950–2021 (see Figure 2). The second largest power deficit event at 1.26 TWh is predicted when using climate data from 1983 – assuming installed generation capacities as in February 2021. Furthermore, we observe 17 minor events. However, the sum of deficits of all 17 minor events is less than 1% of the sum of the deficit of the 9 largest events. We therefore exclude them from the further analysis.

In our model predictions, the loss of load event has a duration of 106 hours, and causes an aggregated deficit of 1.49TWh, at a peak capacity deficit of 31.3GW. There are several events with similar peak capacity deficits identified in the 1950–2021 period, and also events with a comparably long duration but none with a comparably high amount of loss of load. In the largest event before 2021 (1962 and 1983), 250GWh less lost load results from our simulation (Figure 2). 1989 was the last time a similar freeze event occurred. This long break in freeze events of a significant magnitude may explain why the recent event hit an insufficiently winterized power production system.

The 2021 record high loss of load is not caused by the freeze magnitude alone but by a combination of a long, relatively cold freeze event and an inopportune timing of the freeze peak. According to Figure 1 the system failure occurred early and was prolonged by a long freeze period afterwards. This is in contrast to other years when temperatures recovered more quickly after temperature minima had been reached (e.g. in 1951 and 1963). This finding is supported by the extreme value statistics of the freeze spells shown in Figure 3. 2021 was the second longest freeze event in seven decades. It has a return period of 37 years. Other events, however, were colder (1951, 1989) or had higher frost sums (1951, 1983).

In terms of load, the highest predicted winter load in 2021 was slightly lower than the highest predicted winter load in the complete 71 year time series (Figure A.1), as there were lower temperatures in earlier years during the 1989 event.

It may also have been expected that freeze events would have decreased due to global warming. However, our analysis does not show any significant trend in the loss of load time series (Figure A.12). Still, average temperatures in Texas significantly increased due to climate change since 1951 (Figure A.13). This result is confirmed by others, however, the increase in mean temperature is not genuinely transferable to extreme temperatures [10]. A stratified analysis of annual freeze events (minimum annual temperature) below temperature thresholds from 0 to -10 °C reveals that there is indeed no significant observed change of severe freeze events below -2 °C (section A.9). Only very mild freeze events showed a significant attenuation (2.6 °C over the past seven decades), but such events are irrelevant for freeze related failures of the power system comparable to the 2021 event.

Overall, extreme value statistics show that the event of 2021 was severe because of its long freeze duration and its freeze dynamics. Against the background of seven decades of observed climate data, the freeze event had to be expected, especially as we could not find evidence for a decrease of severe freeze events due to climate change. This suggests that similar events comparable to the one in 2021 need to be mitigated even in a future, on average warmer climate.

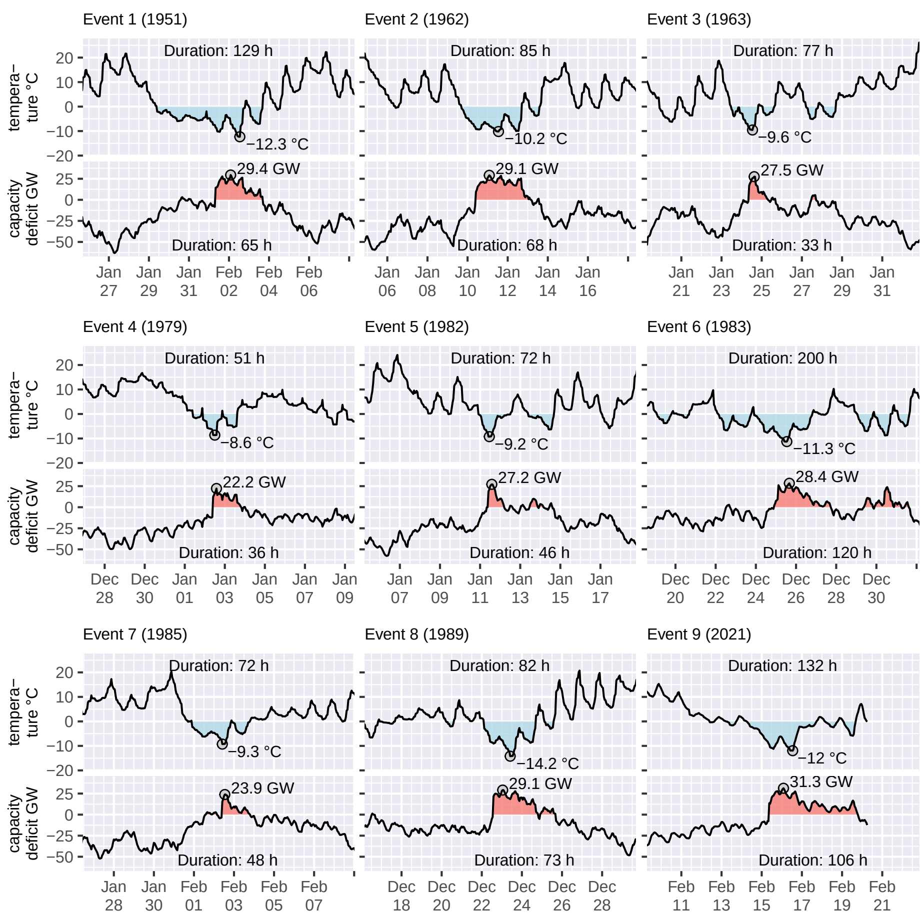

Figure 2: **Analysis of extreme temperatures and simulated loss of load events** Population weighted temperature and predicted capacity deficit of severe freeze events within the 1950–2021 period. Labels in the graph refer to temperature minima and deficit maxima

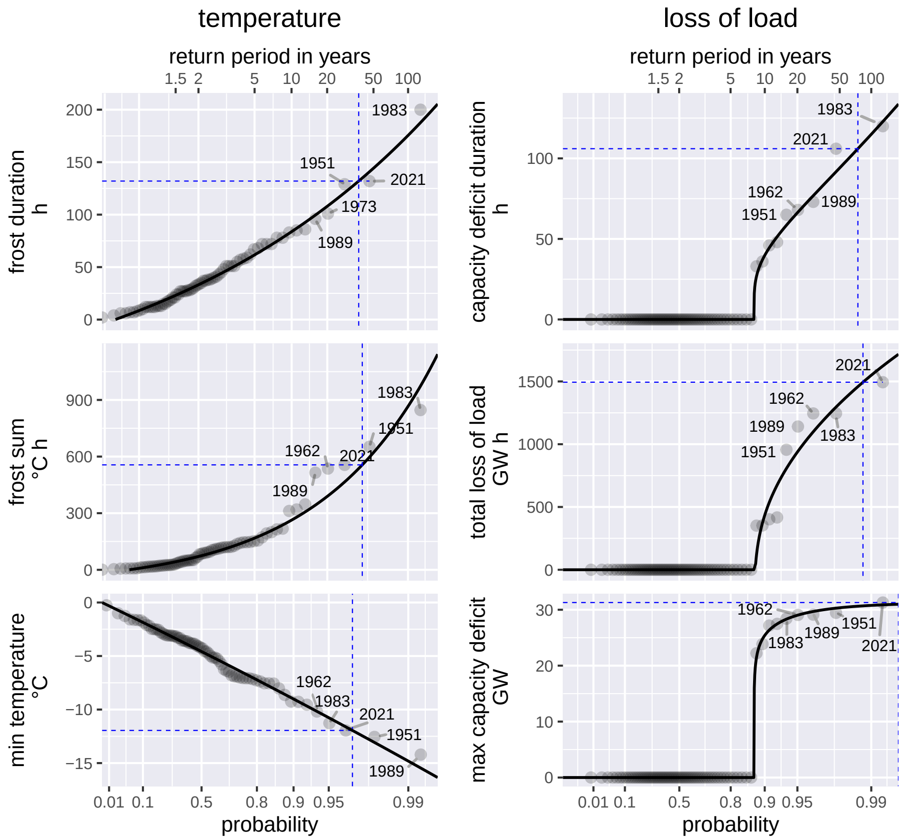

Figure 3: **Extreme value statistics of temperature and power deficits** Population weighted temperature (left panels) and predicted capacity deficit (right panels) of freeze events in Texas from seven decades of of climate data. Shown are the empirical (circles) and theoretical (lines) quantile functions of the three deficit characteristics, duration (upper), severity (centre) and intensity (lower). The return period (inferred from a GEV distribution) and magnitude of the 2021 event are annotated in blue. Very small events lasting less than six hours are removed.

Comparing revenues to costs of winterization

In the following, we assess how much revenues could have been earned by power generators by winterizing their capacities under current regulation, assuming perfect competition, and using the 71 past meteorological years in our simulation. The revenues result from the scarcity price mechanism implemented by ERCOT: it increases prices automatically, if spare capacity falls below a certain threshold [8]. The upper price limit is set to 9000$/MWh if spare capacity is below 2GW (Figure A.11). If power operators winterize, they will be able to generate during times of high scarcity, generating additional revenues.

Revenues from winterization are high, but show significant variability. For the first winterized GW of gas power capacity, expected revenues over a 30 years period are at 1.06bn$/GW, but drop to 0.52bn$/GW at 14GW of winterization (see Figure 4). Revenues for coal power plant winterization are slightly lower per GW, and significantly lower for wind power. For all technologies, the spread of revenues is high: The revenues at the 68% confidence interval are reduced or increased by half of the expected revenues. In 1.2% of all cases, there is no deficit event in a 30 year period, which is the worst case scenario in case of investment in winterization, because no additional revenues from winterization can be earned at all.

Significant winterization measures can be implemented under our estimates of expected revenues, assuming that variable operating costs are low for power generators[2]. In particular, we estimate that the winterization of gas wells – or building 250GWh of pipe gas storage at gas power plant locations – in combination with winterization of gas power plants will cost about 450M$/GW (see section A.10). This cost is below the revenues up to the 15$^{\text{th}}$ Gigawatt of winterized capacity. Winterization of coal and wind power plants is significantly cheaper, as no or very limited fuel supply infrastructure would have to be winterized. Winterization costs assumed at 10% of initial plant investments of coal power plants are far below revenues up to full winterization of all failed coal capacity. In fact, one could even assume winterization cost of 30% of initial plant investments and winterization cost would still be lower than the revenues for the completely winterized capacity. For wind turbines, our estimates of revenues are half those of coal, but are still substantially higher than the costs of winterization which are reported to be 5% of investment costs [11].

The assumed discount rate has a significant impact on results. When increasing the rate from 5% to 10%, the revenues for winterizing the first GW of gas power plants are reduced from 1.06bn$ to 0.65bn$. While winterization of coal and wind power still fully pays off under these assumptions due to low winterization cost, the profitable winterization of gas infrastructure and gas power is reduced from 15GW to 7GW.

Before 2021, these estimates might have been lower, as since 1989 no climatic event of a similar magnitude was observed. When dropping 2021 from our set of events, our estimates of expected revenues falls by 17.6% on average, causing only 13GW of gas power to be profitably winterized. Still, when taking into account expected revenues, a significant amount of capacities should have been winterized.

Further assessments of the uncertainties in our modeling approach can be found in Appendix A.2.

Potential reasons for the lack of winterization

We have shown that the Texas loss of load event in February 2021 was among the top three extreme events when simulating the power generation system under climate conditions of the last 71 years. Nevertheless, winterization of power generation infrastructure was already profitable before the event took place, taking into account the past climate, potential climate-change impacts, and current regulatory conditions. So why did power generators not winterize? We identify several possible reasons for this gap between potential revenues and observed winterization efforts.

[2]This is true for nuclear, wind, PV, and coal power plants. However, gas power plants may face high gas spot market prices during cold spells, as observed during the 2021 event. We assume here that gas plant operators therefore have physically or financially hedged against high gas prices.

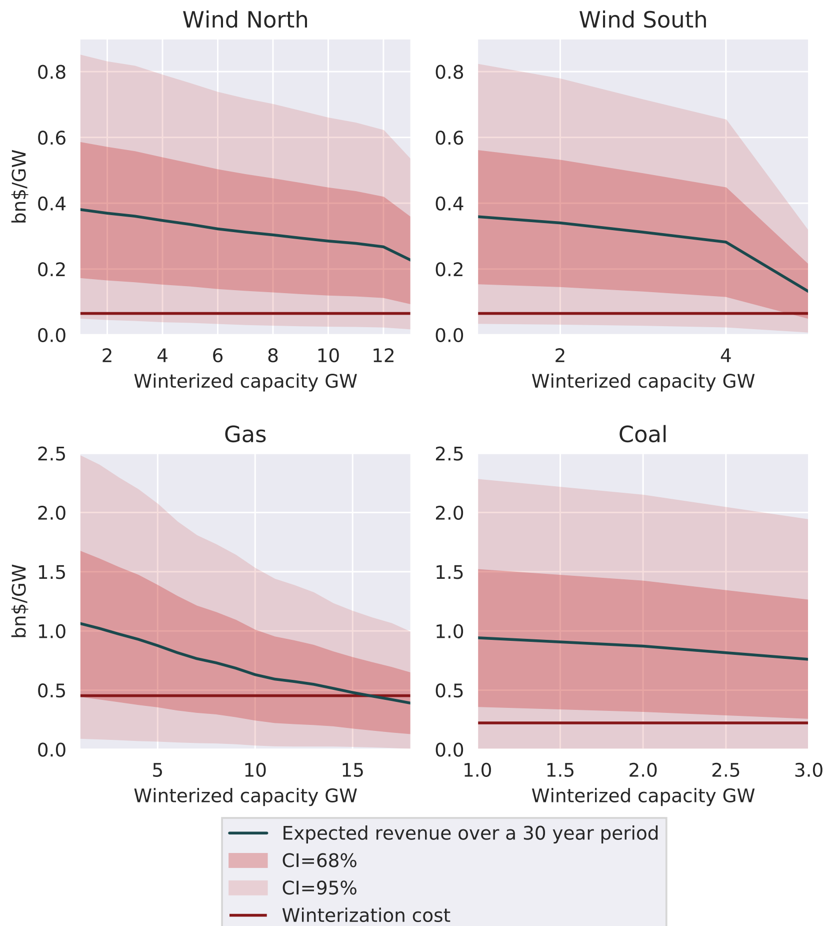

Figure 4: **Revenues from winterization** Comparison of revenues (bn$/GW of winterized capacity in a 30 year period) to marginal costs for winterizing existing power generation capacity

First, while expected revenues are above winterization costs, their variance is high, in particular for gas power plants: for this technology, for the winterization of the first GW in 16% and for the winterization of the 10th GW in 36.2% of all cases, the profit becomes negative. Additionally, gas power plant owners have to secure gas supply and may be exposed to high gas prices during cold spells. However, the risk of not investing into winterization is very low. Even if a catastrophic failure occurs, the associated social cost is not born by power generators. Potential costs include minor fines and damages to power plant equipment. A risk-averse investor may therefore decide against winterization. For coal and gas power plant owners, another fact may reduce expected revenues: we assumed a 30 year lifetime for all power plants, but gas and coal generation infrastructure is partly old and winterization now may not pay off as the plants may be retired soon anyhow. For wind power plant owners, we see however the highest incentives and the lowest risk: the fleet is comparably young, winterization cost is low, and revenues are well above these costs. Even under relatively high risk-aversion, winterization seems to be a rational choice for wind power plants therefore, in particular if new wind parks are built.

Second, even though historical temperature time series clearly indicate that the 2021 event could have been expected, the associated outages of power plants may have been underestimated by power generators. This is supported by King et al. [12] who show that for a high number of plants, rated temperatures of failing power plants were partly significantly lower than prevailing temperatures during outages in February 2021. As no major outage as the one in February 2021 was observed before, plant owners may have assumed that current power plant standards are reliable enough.

Third, high discount rates also imply that winterization becomes significantly less attractive. At a 10% discount rate, our estimates of revenues drop by about 38.8%. Therefore, alternative investments with higher return on investment and potentially lower risk may be preferred under limited capital availability, in particular for the more costly winterization technologies necessary for gas power generation.

Fourth, our calculation only holds under perfect competition. Owners of large generation assets have less incentives to additionally winterize, as this would partly reduce scarcity prices for the already winterized part of their fleet. However, there is little concentration in the market in Texas and we therefore see strategic behaviour potentially as less important reason (see Appendix A.3).

Conclusions

The total cost to society of extreme freeze events has to be expected to be at least one order of magnitude higher than winterization cost. Winterization is therefore highly welfare enhancing. We have shown that current regulation in principle gave sufficient incentives for a larger scale winterization, but risk aversion, lack of knowledge about potential outages, or higher yielding alternative investments may have impeded generators from taking more efforts. A more stringent regulation of winterization therefore seems to be necessary. In June 2021, Senate Bills 2 and 3 became effective. They enforce winterization of power plant infrastructure. However, gas power plants do not have to fully winterize but instead, a committee will define those assets which have to do so [13]. As the failure of the gas power infrastructure by far has the largest impact on deficits in our simulations, we emphasize here that this should be strongly considered when defining rules for enforcing winterization of a large share of gas power plants and associated infrastructure.

Winterization of power generation units, however, may also come with its downsides during periods of warm temperatures, as measures used to increase performance during cold weather, such as integrating gas turbines into insulated buildings, may make the cooling of power plants more complex. Apart from winterization, other mitigation measures, in particular strong demand response programs and an expansion of transmission capacities to neighbouring states may therefore become important [6]. They may be significantly less costly, and they will be beneficial not only during cold spells. Both options can make the system more resilient against other variations in power generation, in particular taking into account the ongoing transition to a larger share of renewable energies in the power generation mix. During extreme freeze events, demand response may have to focus on industrial applications however, since electric heating can hardly be postponed during freeze events.

Of course, our results have to be considered in the light of a continuously evolving power system. We assume 30 years of lifetime for all installed capacities, however some capacities, in particular coal power plants, may soon be retired and their winterization may not be profitable therefore. As winterization of new capacity is cheaper and easier to implement than winterization of existing one, winterization standards for installing new power plants and associated infrastructure should have high priority. The ongoing transformation of the Texan power system can therefore be considered an opportunity to ensure robustness during future freeze events.

Methods

We use a chain of statistical and simulation models to derive loss of load events, and revenues from winterization. The data sets which feed the models and model interactions are shown in Figure 5. A detailed explanation of all involved models and data sets is given below.

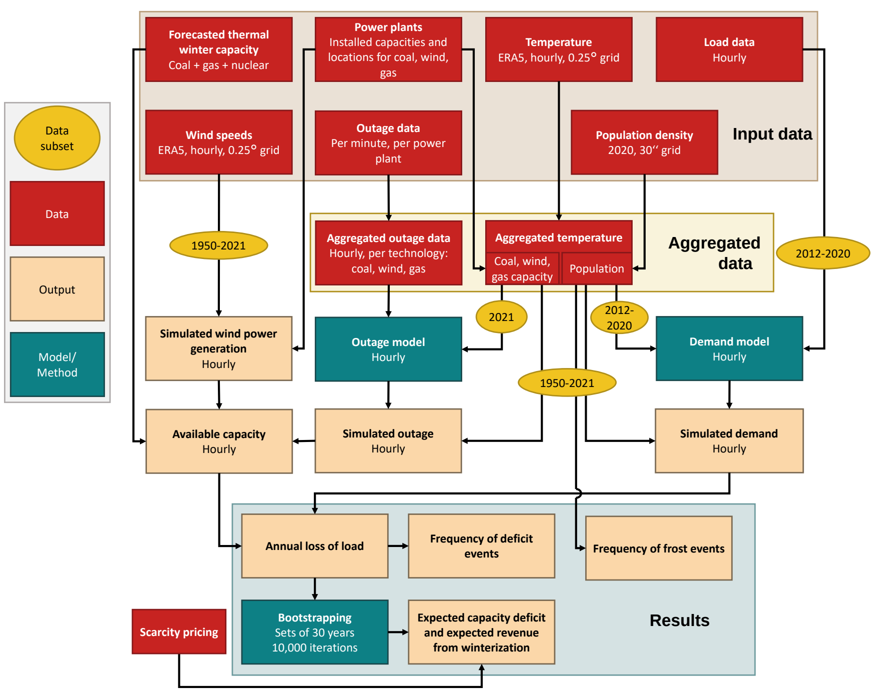

Figure 5: **Overview of data inputs and deficit model**

Estimation of temperature induced electricity deficits: To estimate the amount of deficits in the power system, we simulate the difference between the expected, temperature dependent electricity demand and the available generation capacity.

Formally this can be described by defining the capacity deficit $d_{y,h}$ as the difference between the demand$_{y,h}$ and the available generation capacity $c_{y,h}$ in year y in hour of year h:

$$d_{y,h} = \text{demand}_{y,h} - c_{y,h} \tag{1}$$

The total loss of load d_y^{tot} in a year is the sum over $d_{y,h}$ for all hours where capacity deficit was larger than 0:

$$d_y^{\text{tot}} = \sum_{\substack{h,\\ \mathrm{d}_{y,h}>0}} d_{y,h} \tag{2}$$

Demand is simulated from load in the past using a linear regression model as described below in more detail. Available generation capacity is obtained by reducing the total available capacity by temperature dependent outages:

$$c_{y,h} = c^{\text{thermal}} - o_{y,h}^{\text{gas}} - o_{y,h}^{\text{coal}} + \frac{w_{y,h}}{c^{\text{wind}}}\left(c^{\text{wind}} - o_{y,h}^{\text{wind}}\right) \tag{3}$$

where c^{thermal} is the total available thermal capacity in winter according to ERCOT, and $o_{y,h}^{\text{gas}}$, $o_{y,h}^{\text{coal}}$ and $o_{y,h}^{\text{wind}}$ are the temperature dependent power plant outages, respectively. Current wind power generation $w_{y,h}$, simulated from wind speeds assuming full capacity (for details refer to [14]), is used to calculate the capacity factor and scale the working wind power capacity, i.e. the difference between installed capacity c^{wind} and wind power outages $o_{y,h}^{\text{wind}}$. We do not model nuclear and solar PV outages, as their overall generation capacity and their contribution to outages was low (Figure 1). We also neglect transmission of power from neighbouring states, which is of minor magnitude.

According to ERCOT [15], 67.5GW of capacity was available during the 2021 winter, but 4GW of these may have been under maintenance. We therefore assume a value of 63.5GW for c^{thermal} to match our simulation with available capacity during the event, as indicated by served load.

Demand prediction: We predict demand$_{y,h}$ from temperatures using a regression model (equation (4)). We estimate a model for demand in winter (December–February, the three coldest months on average) from load data in the years 2012–2020, taking into account a linear time trend $l_{y,h}$, seasonality (sine and cosine terms depending on the hour h of the year y), and the temperature $t_{y,h}$. Furthermore, we include dummy variables for the hour of day $\delta_{i,y,h}^{\text{hod}}$, the weekdays $\delta_{i,y,h}^{\text{dow}}$, and for holidays $\delta_{y,h}^{\text{hold}}$. To account for changes in the temperature dependency of load over time due to installment of increased shares of electrical heating, we include the interaction of the linear time trend with temperature. We also include $t_{y,h}^2$ and $t_{y,h}^4$ into the equation as with falling temperatures, load shows a highly non-linear increase (Figure A.5). In order to avoid overestimation of loads at low temperatures with this model, a threshold temperature at -8°C was introduced, under which the temperature dependency of the load was kept constant (see Figure A.5).

$$\begin{aligned}\text{demand}_{\mathrm{y,h}} = \beta_0 + \sum_{i=1}^{7} \beta_i \delta^{\mathrm{dow}}_{i,y,h} + \sum_{j=8}^{31} \beta_j \delta^{\mathrm{hod}}_{j,y,h} + \beta_{32} \delta^{\mathrm{hold}}_{y,h} + \\ \beta_{33} \sin\left(\frac{2\pi h}{8760}\right) + \beta_{34} \cos\left(\frac{2\pi h}{8760}\right) + \beta_{35} l_{y,h} + \\ \beta_{36} l_{y,h} t_{y,h} + \beta_{37} t_{y,h} + \beta_{38} t^2_{y,h} + \beta_{38} t^4_{y,h}\end{aligned} \tag{4}$$

The model performs well for different temperature ranges in terms of average bias (Figure A.6), although at low temperatures we slightly underestimate load. We therefore also ran the whole model with an alternative demand model where the temperature impact does not flatten off at -8°C. The results are reported in our sensitivity analysis, indicating that the estimated deficits do not strongly change when using a different demand model (<10% difference). Testing the model out-of-sample for January 2021 delivers a high fit with an R^2 of 0.92 and an RMSE of 1.31 GW. A cross-validation for other years (see Table A.1) indicates a good fit in general.

Temperature dependent generator outages: The power plant outages in Texas were caused by a systemic failure, as a substantial amount of capacity tripped in a short period of time [9]. Most of the capacity failed due to weather events, but the lack of fuel supply was also relevant. Additionally, non- weather related equipment failures and, to a smaller amount, frequency problems in the grid caused problems at generation units. This implies that temperature at single power plants alone cannot fully explain outages. We derived infrastructure fragility curves [16] from our data and they show that 25% of gas power plants, about 30% of wind power plants, and 50% of coal power plants failed when temperatures were above 0°C and in many cases have not been below 0°C in the days before failure. Other weather conditions besides freezing temperatures may be partly responsible, but at least wind conditions at the time of failure were not particularly extreme. Besides freezing temperatures, which caused failure of power plant components and of gas production and gas distribution, there are also systemic reasons for failure therefore.

We do not use infrastructure fragility curves for modeling outages, but estimate threshold temperatures and outage capacities during catastrophic failure by technology: we derive the temperature, at which the largest increase in outages occurred, from the 2021 outage data. Furthermore, we estimate an outage level in terms of tripping capacity. Finally, we also define a constant recovery rate, which describes how outages decreased after the recovery temperature is reached. This is an aggregate approach and will omit smaller outages, but it accounts better for the inter-dependency of failures. A detailed outline of how we derived the outage parameters from the 2021 data in Texas is given in section A.5. The resulting outage models are subsequently applied to the 71 years of climate data to obtain capacity availability during this period.

Estimating revenues from winterization: We determine the revenues from the scarcity price mechanism implemented by ERCOT [8]. This mechanism comes into effect, whenever spare capacity falls under 8GW. In this case, power market prices are regulated and set to fixed (high) values depending on the spare capacity. The lower the spare capacity, the higher the price, reaching 9 000$/MWh when spare capacity falls under 2GW (see appendix A.6). We determine spare capacity $s_{y,h,g,z}$, g being the technology used for power generation which is winterized (i.e. gas, coal or wind) and z being the amount of winterized capacity, by

$$s_{y,h,g,z} = c_{y,h} + a_{y,h,g,z} - \text{demand}_{y,h}, \tag{5}$$

where $a_{y,h,g,z}$ is the additional capacity available at a certain point in time. For coal and gas, $a_{y,h,g,z}$ equals the amount of winterized capacity z when the outages are larger than z. In periods without outages before winterization of power generation capacity, $a_{y,h,g,z}$ is 0GW. During outage events, the available capacity is increased by the amount of winterized capacity z for gas and coal power plants. If the outage $o^g_{y,h}$ is smaller than winterized capacity z, then additional capacity corresponds to the outage capacity, i.e. $a_{y,h,g,z} = \min(z, o^g_{y,h})$. For wind power plants, the additional capacity is calculated by multiplication with the capacity factor similarly to equation (3):

$$a_{y,h,\text{wind},z} = \frac{w_{y,h}}{c^{\text{wind}}} \cdot \min\left(z, o^{\text{wind}}_{y,h}\right) \tag{6}$$

We use temperature data for all years in the period 1950–2021 to determine $\text{demand}_{y,h}$, we use simulated wind power generation for the same years from ERA5 reanalysis wind speeds to obtain $w_{y,h}$ (for further details see [14]), and we use the temperature dependent power plant outage functions to estimate $o^g_{y,h}$. This allows to simulate today's power system for 71 different weather years as a set of different weather realisations. Consequently, we calculate the market price $p_{y,h,g,z}$ by

$$p_{y,h,g,z} = f(s_{y,h,g,z}) \tag{7}$$

The function f maps spare capacity to scarcity prices as used in the price regulations by ERCOT (see Appendix A.6). We assume that the market price is 0 whenever there is no capacity scarcity. This of course is a simplification, but is a sufficiently precise approximation for our purpose[3]. We estimate the revenues from winterizing one additional unit of capacity. This capacity may not fully be dispatched in all hours with scarcity prices, we therefore determine $c^{\text{dispatch}}_{y,h,g,z}$ as being the dispatched capacity in a particular hour. Let $d_{y,h,z}$ be the deficit in winterization scenario z, where all values < 0 are set to 0. Then, $c^{\text{dispatch}}_{y,h,g,z} = d_{y,h,z-1} - d_{y,h,z}$, i.e. the dispatched capacity is the difference in capacity deficit between two consecutive winterization scenarios. The revenue $r_{y,g,z}$ earned by that additional unit in a year y is hence defined by

$$r_{y,g,z} = \sum_h p_{y,h,g,z} \cdot c^{\text{dispatch}}_{y,h,g,z} \tag{8}$$

We further assume that additionally winterized capacities are dispatched last in the merit-order during deficit events. This implies that additionally winterized capacities can only earn revenues during deficit periods in former winterization scenarios, i.e. when the price is at 9,000\$/MWh[4]. If the dispatch order would be changed by winterization, this would imply higher revenues for winterization of new capacities, making our estimates (slightly) conservative.

[3] We analyze only scenarios with winterization, no additional capacity is installed. Winterization will only affect dispatch and market prices during outages of power plants, so market prices during other periods should remain unaffected, implying no additional revenues from winterization during normal operation.

[4] We use, however, the same method also for determining marginal revenues in non-competitive markets in Appendix A.3. For that purpose, the full range of function f is relevant.

We then use the set of revenues $r_{y,g,z}$ derived from 71 different weather realizations for a bootstrapping procedure. For each bootstrapping iteration b, we sample 30 years of revenues $r^{\text{boot}}_{i,b,g,z}$ for $i = 1, \dots, 30$ from the set $r_{y,g,z}$, $y = 1950, \dots, 2021$. This is done for 10 000 iterations, $b = 1, \dots, 10\,000$. Subsequently, total revenues $R_{y,g,z}$ over a typical investment period of 30 years are calculated, as shown in equation (9), $i = 0.05$ being the discount rate:

$$R_{b,g,z} = \sum_{j=1}^{30} r^{\text{boot}}_{j,b,g,z}(1+i)^{-j} \tag{9}$$

This results in 10 000 different samples $R_{b,g,z}$, allowing to derive a distribution of revenues from winterization. We emphasize here that this calculation only holds under a perfectly competitive market, as we assume marginal winterization steps of 1GW. For generators with large capacities, partly already winterized, additional winterization may yield strongly negative revenues, as market prices for existing winterized assets are reduced by the additional winterization. We discuss this in more detail in appendix A.3.

Frequency analysis of freeze and power deficit events: The frequency analysis of extreme events follows well-established methods of hydrological drought analysis [17], where deficit events are defined as periods when the variable of interest is below a certain threshold. Here, we use two different threshold concepts. First, we analyse temperature, and define a constant threshold of 0°C to define deficit events in analogy to drought events in drought statistics. Deficit events in the power system, resulting from low temperatures, are simply defined for periods when the capacity deficit > 0GW (equation (1)). In each case, the result is a derived deficit time series, which is further investigated using Yevjevich's theory of runs [18]. During a freeze period, minor thaw episodes or other disturbances may split an event in several smaller events. As a remedy, pooling procedures have been recommended [19]. In this study, an inter-event time criterion of 1 day is used to define the deficit event series. In case that multiple events occur in a year the event with the absolutely largest accumulated deficit is used for further analysis. The series so derived are characterized by three deficit characteristics: duration (measured in hours), intensity (minimum temperature / maximum power deficit), and severity (aggregated frost sum / power deficit over the event), each of which constitutes an annual extreme value series. These are further analyzed using extreme value statistics to determine the return period of each freeze and capacity deficit characteristic according to natural hazard management standards. Minor capacity deficit events (with a duration < 6 hours) are excluded as these are not extreme events and would distort extreme value modeling. Our analysis was conducted using the R-software package lfstat [20], which provides a collection of state-of-the-art methods that are fully described in the World Meteorological Organization's manual on low flow estimation and prediction [21]. The resulting winter power deficit events are shown in Figure 2, their extreme value statistics are shown in Figure 3.

Data: Temperature at 2m above ground is taken from the ERA5 reanalysis [22]. We weight temperature over Texas by population density [23] to derive a temperature index for modeling electricity demand. For estimating outages in the power system due to low temperatures, we also weight temperature by capacities of wind [24], coal and natural gas power plants [25], which were the power generation technologies most affected by failure during the extreme temperature event of February 2021. For wind power plants, we split into a North and South region (along the latitude of 30°), since temperatures at wind parks in the North and South of Texas differ substantially. Since the failure of the power system might be related to infrastructure at gas fields supplying these power plants [26], we also determine a gas field weighted temperature index, using the distribution of natural gas production by county [27] to complement our analysis. Load data used for demand prediction were retrieved from ERCOT [28] for the period 2004–2021/02. Since the focus of this study is on freeze events in winter, only winter load data (Dec–Feb) is used. Outage data is provided in the period since 10^{th} of February 2021 by ERCOT [29] and is aggregated by power generation technology for the analysis.

Data availability

We will provide aggregated climate data from ERA5 as well as gridded population data necessary to derive population weighted temperatures openly to the community on Zenodo. Data from public institutions, in particular ERCOT, the Energy Information Administration, and the Texas Railroad Commission is not available under an open license. However, we will provide, upon publication, links to data sources and the whole code, including download scripts, so that our analysis, and in particular all figures, can be fully reproduced.

Code availability

Code will be published in a Github repository and will be archived using Zenodo, hence a DOI for the code can be provided too.

Corresponding author

Katharina Gruber

Acknowledgement

We gratefully acknowledge support from the European Research Council ("reFUEL" ERC2017-STG 758149). We are grateful to Edgar Virgüez who provided spatial locations of power plant outages and discussed early results with us.

Contributions

Conceptualization: K.G., T.G., P.R., G.L., J.S.; Software: K.G., T.G., P.R., J.S.; Investigation: K.G., T.G., P.R., G.L., J.S.; Writing - Original Draft: K.G., G.L., P.R., J.S.; Writing - Review & Editing: K.G., T.G., , G.L., P.R., J.S.; Visualization: K.G., T.G., P.R.; Supervision: J.S.; Funding acquisition: J.S.;

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List of Figures

A Appendix

A.1 Load and temperature extremes

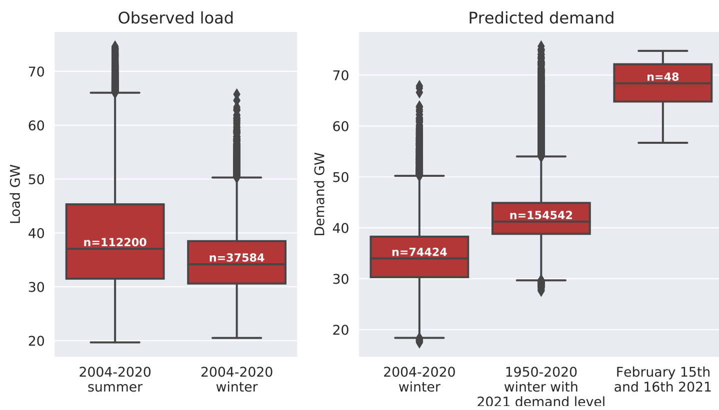

Figure A.1: **Loads and predicted demand in a long-term context** Observed loads for 17 years (2004–2021/01) for winter (Dec–Feb) and summer (Mar–Nov)) periods, predicted winter loads for 17 years (2004–2021/01) and 71 years (1950–2021/01) with demand level of 2021 and extreme loads on February 15th and 16th 2021. White numbers indicate the number of observations (hours).

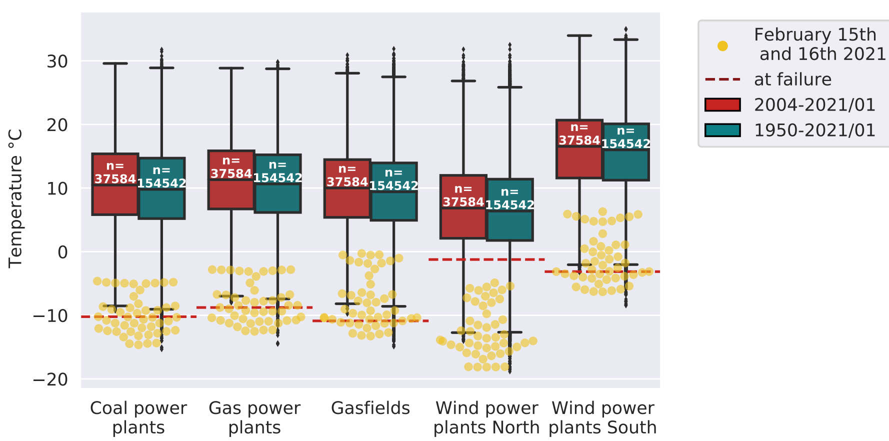

Figure A.2: **Temperatures in a long-term climatic context** Winter temperatures weighted by natural gas and power plant capacity, gas field production and wind power plant capacity in North and South Texas compared to temperatures during the February 2021 event. Numbers in white indicate the number of observations (hours)

A.2 Model uncertainty

Outage data: We calibrate our outage model against the outage data provided by ERCOT for the 2021 event, i.e. against one single event. This data basis is of course limited. The provided data additionally may be incomplete or contain errors – and ERCOT does not provide outage reasons by power plant. Aggregated information is available and it shows that most capacities failed due to weather related reasons, but in particular gas power plants were also affected by limited gas supply [30]. This cannot be modelled explicitly by us due to the lack of data.

However, we do not aim at predicting outage probabilities of single plants, but catastrophic events with widespread outages. In particular for gas and coal power plants, outage temperatures estimated by us are at the very lower end of temperatures observed in the period 2004–2021, confirming that most probably at higher temperatures no major outages should be expected. However, for wind power in Northern Texas the outage temperature is comparably high and the large scale failure of wind power plants in February 2021 may have additional, unidentified reasons. As outages of Northern wind power plants alone, however, do not cause large capacity deficits, our estimates of large-scale deficits do not strongly depend on that temperature. It shall be mentioned, however, that some of the smaller deficit events are caused by failure of wind power capacity, and therefore we explicitly limit the analysis to the 9 major events.

Nevertheless, we tested our model with different outage and recovery temperatures and found that only gas outages have a major impact on total deficits (see Figure A.3). Estimates of loss of load events – and therefore of revenues – depend mainly on the assumptions on outage temperatures for gas power plants, as their failure has by far the biggest impact on the magnitude of loss of load events. An increase in outage temperatures from -8.8°C to -8.0°C, i.e. the minimum temperature in the period 2004–January 2021, increases loss of load from 7.57–8.05TWh to 8.80–9.34TWh in 71 years, depending on the respective recovery temperature. This is of minor magnitude. Much higher outage temperatures, although shown in the Figure, are unlikely, as such temperatures have been frequently observed in the last decade, but did not trigger major outage events. Anyhow, our main conclusions are not affected if outage temperatures are higher than assumed by us: this would actually increase potential revenues from winterization and therefore make it even more attractive. In contrast, the outage temperatures assumed for wind and coal power plants have a minor impact on the estimates of loss of load, if they are changed for 3°C up or down for one technology only (in the range of 6.64–8.24TWh). A concurrent increase of outage temperatures of all power generation technologies changes loss of load from 7.44–8.12TWh to 9.70–10.56TWh when increasing the outage temperature by 1°C. For all technologies, assumptions on recovery temperatures do not change our estimates of loss of load significantly, as loss of load shows less than 1TWh difference within a variation of recovery temperature of 3°C. Lowering outage temperatures for all technologies decreases our estimates likewise. For a temperature decrease of 1°C, the loss of load predictions are a third less than our base estimate (5.27–5.74TWh). However, as outages have occurred at higher temperatures in 2021, such a scenario is unlikely.

Our finding that 2021 was the largest simulated loss of load event in the period 1950–2021 is insensitive to the assumed outage and recovery temperature. If outage temperatures of power plants are simultaneously increased by 1°C, 2021 remains the largest event. Furthermore, while the total number of outage events differs when outage temperatures are changed by 1°C, the nine major events continue to be the largest events.

We did not simulate the relationship between damages during winter and associated power plant outages during summer due to increased maintenance or lower plant reliability, as observed in Texas in Spring/Summer 2021. This would further increase our estimates of revenues from winterization of power plant assets.

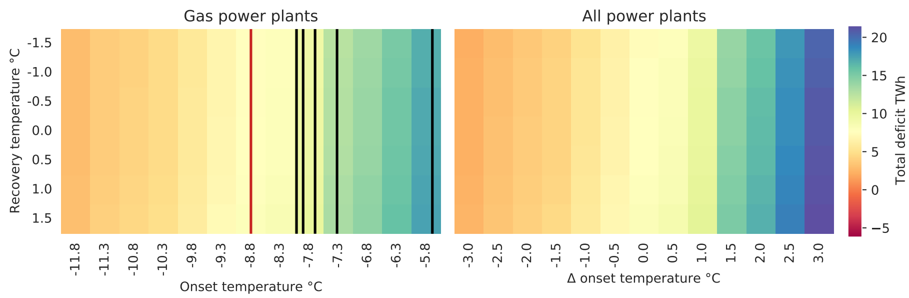

Figure A.3: **Senstivity analysis of onset and recovery temperatures** Sensitivity of the accumulated loss of load between 1950 and 2021 by generation type to onset temperature and recovery temperature used in the outage model for a variation of gas threshold temperatures (left) or all threshold temperatures together (right). Black lines show the yearly temperature minima in the period 2004–2020, and the red one the threshold temperature given by the outage model

Climate change: While it is certain that climate change affects average temperatures, our analysis indicates that it may not have caused a trend of decreasing extreme freeze events. Nevertheless, we assessed how the number and magnitude of power deficit events would change if temperature extremes would follow the same trend as average temperature. Under such assumptions, we find that the loss of load drops from 7.66TWh to 6.80TWh and 5.92TWh, assuming 2021 and 2050 as years for simulation, respectively (see section A.9 for modeling details). We emphasize here that our approach is in contrast to observations (see A.7) and should only be understood as sensitivity analysis. Nevertheless, even under such a scenario, the loss of load is still significant and – a however reduced – extent of winterization would be profitable.

Load: the uncertainty in the demand model is high in particular at low temperatures, as there is very limited data to train on. In fact, only the forecasts from ERCOT during the 2021 deficit event are available – but the uncertainty in different ERCOT forecasts itself is high. We have therefore taken a conservative approach which cuts the impact of temperature at -8°C. This fits well to ERCOT forecasts (see Figure A.5). However, we have also tested a demand model where load is allowed to increase, following the fit of the demand model, even below -8°C. This increases our estimates of lost load by 8.3%, which gives even stronger support to our finding that investments would have paid off. However, such a demand model has a worse fit to the ERCOT forecasts and it is more likely that some flattening off of demand is occurring at some point, as installed equipment consuming electricity is strongly limited. Also, implicit (e.g. failing logistics during low temperature events causing reduction of industrial output) or explicit demand response may take place at such low temperatures, implying an upper level of load on the network.

Market model: Furthermore, we do not account for changes in the merit order due to winteriziation: this can have effects as scarcity prices are effective even when there is positive, but low spare capacity, i.e. there might be a change in the dispatch order of power plants, allowing for slightly higher profits for some plants, pushing others out of the merit order. For all plants combined, this effect should be however negligible.

A.3 Strategic incentives under winterization

In principle, power generators may strategically decide to not winterize as additional winterization may decrease their marginal revenues if parts of their fleet is already winterized. Figure A.4 shows that for the first additionally winterized Gigawatt, marginal revenues fall below 0, if the company owns more than 20GW of winterized capacity. If even more capacity is winterized, marginal revenues fall even stronger in the amount of owned winterized capacity. However, we deem strategic behaviour as unlikely reason for non-winterization. There are 541 power generating companies in Texas, and the largest owns only 6%, i.e. 6.5GW, of generating capacity [31]. So even if large parts of the fleet of the largest company were winterized, the incentive for further winterization is still high, as marginal revenues are above 0. And due to the low market share, non-winterization by the largest company due to strategic behaviour cannot impede winterization of other companies. Only under explicit collusion of large players, this would be possible.

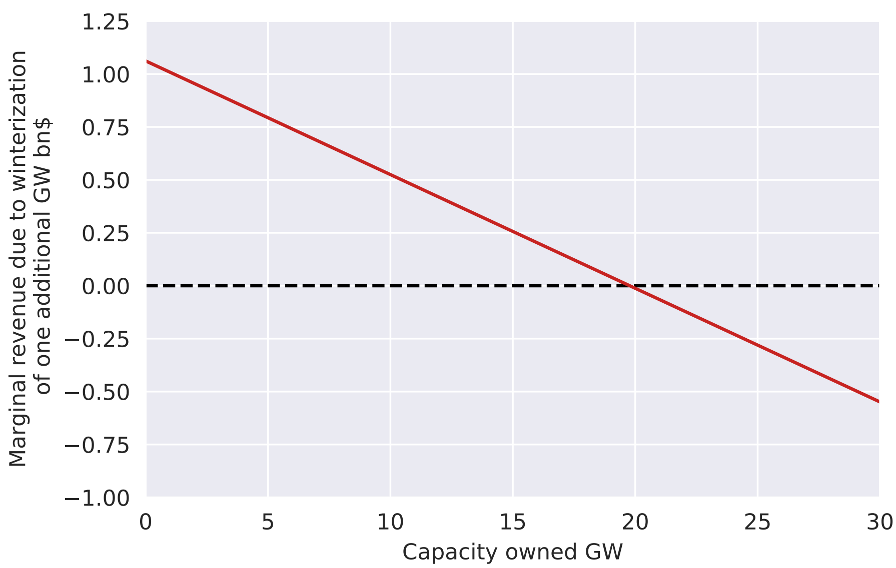

Figure A.4: **Marginal revenues for a large-scale power generator** Marginal revenues from winterizing 1 additional GW of gas power plant capacity, depending on how much already winterized capacity is owned by a company

A.4 Visualization and validation of demand prediction model

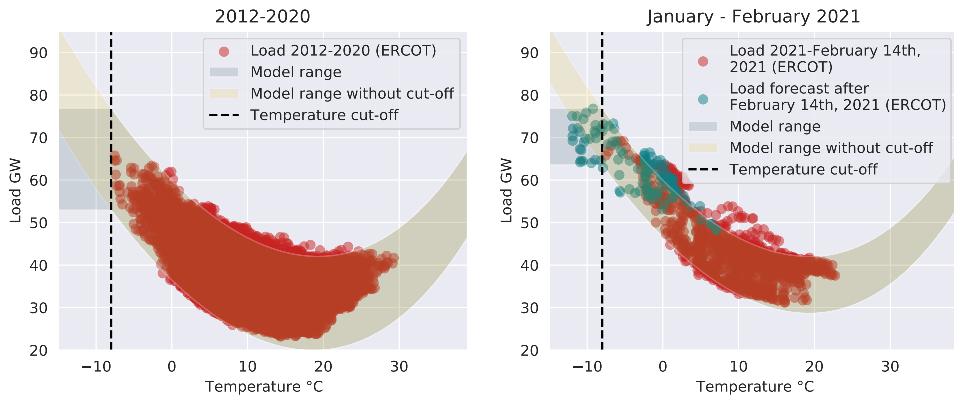

Figure A.5: **Demand model fit:** Predicted load for Winter 2012–2020 data (left) and January - February 2021 data (right). The time parameter (i.e. time trend, type of day dummies and hours) dependent range of estimates is shown once for a model with cut-off at 8°C and once for a model without cut-off.

Table A.1: **Cross-validation of demand model:** Statistical parameters (correlation, RMSE and R^2 for each of the validation years, for 2012–2020 the months January, February and December are validated, for 2021 January only

Year	Correlation	RMSE	R^2
2012	0.95	1.46	0.9
2013	0.96	1.65	0.9
2014	0.96	1.74	0.92
2015	0.95	1.89	0.87
2016	0.94	1.71	0.87
2017	0.95	1.79	0.89
2018	0.96	1.88	0.9
2019	0.94	1.62	0.87
2020	0.94	1.58	0.87
2021-01	0.96	1.31	0.92

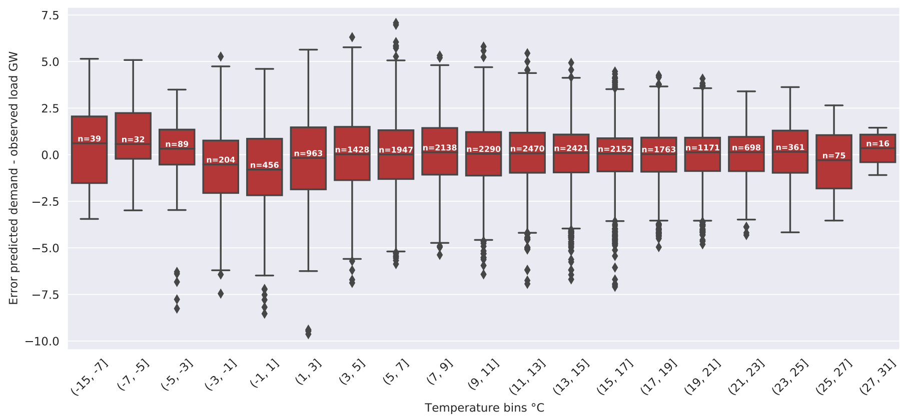

Figure A.6: **Temperature binned differences between predicted demand and observed load** applying the regression model estimated for the years 2012–2021. White numbers indicate the number of observations (hours) for that range

A.5 Approximation of outage functions

We model the outages of the sum of capacities by technological group, defining an outage model with 4 segments: (1) constant outage level before major critical failure, (2) constant outage level during critical failure, (3) declining outage in recovery period, and (4) constant outage level after recovery period (see Figures A.7 to A.10).

(1) The level of the first segment is defined by the first data point in the outage time series. The first segment ends when the single largest increase in outage within one hour occurs (i.e. the maximum of the first differences of the outage time series). The average power plant capacity weighted temperature at that point is defined as outage temperature. (2) The second segments starts at that point and ends when the temperature increases above the recovery temperature, which is set to 0°C consistently for all technologies. However, we neglect any hours with temperatures above the recovery temperature within the first 10 hours after the start of the second segment. The level of the plateau is derived by ensuring that the area below the real outage curve is the same as the area below our modelled outage.

(3) and (4) We extract the outage data from the point of recovery to the end of the timeseries on the 25$^{\text{th}}$ of January. We then fit a model to the data, which minimizes least squares. It contains two segments: one falling recovery segment, and one constant segment at the end of the timeseries - the level of that constant segment is defined as the average of the last ten points in the time series. For segment (3), we can derive a slope after fitting, which is used as parameter to simulate recovery.

These models are applied to the whole 71 year long time series of temperature data, removing the constant outages at the beginning (1) and the end (4). An outage starts in the model, whenever the power plant capacity weighted temperature falls below the outage threshold. The full outage lasts until the temperature increases above the recovery temperature, but at least 10 hours. From that moment on, a linear, falling outage is assumed, until the outages is reduced to 0GW.

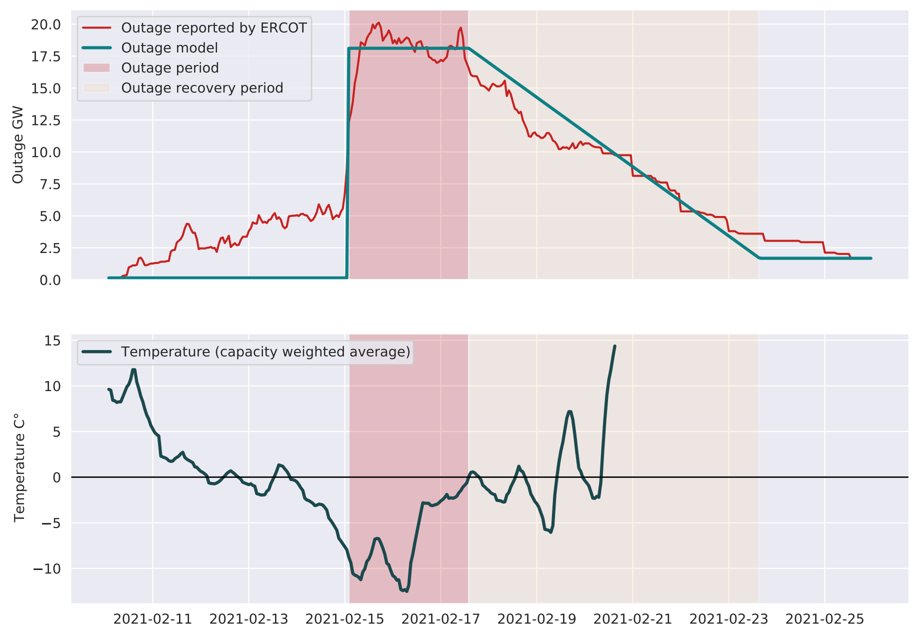

Figure A.7: **Gas outage approximation** Gas outages and temperature at gas power plants and approximated outage model

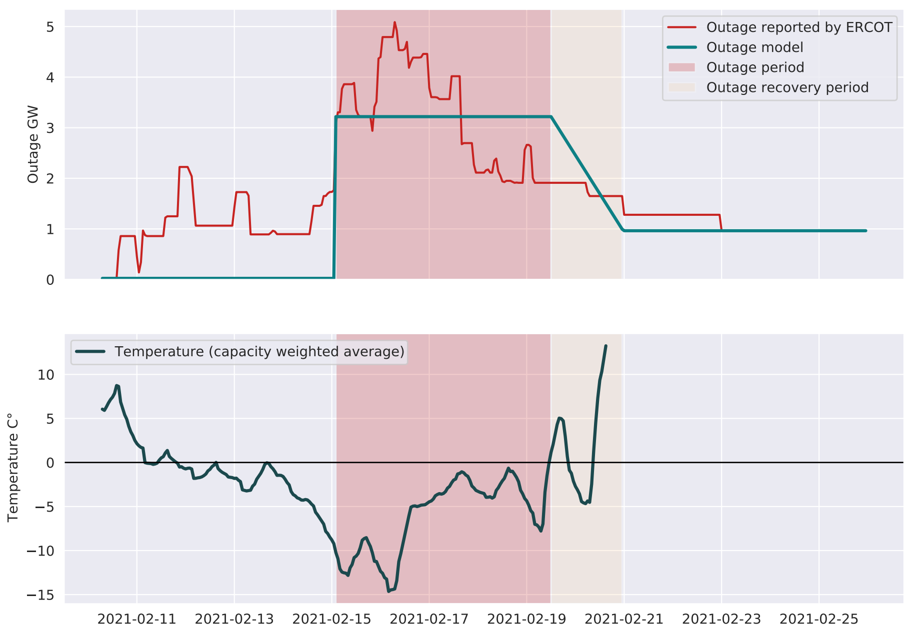

Figure A.8: **Coal outage approximation** Coal outages and temperature at coal power plants and approximated outage model

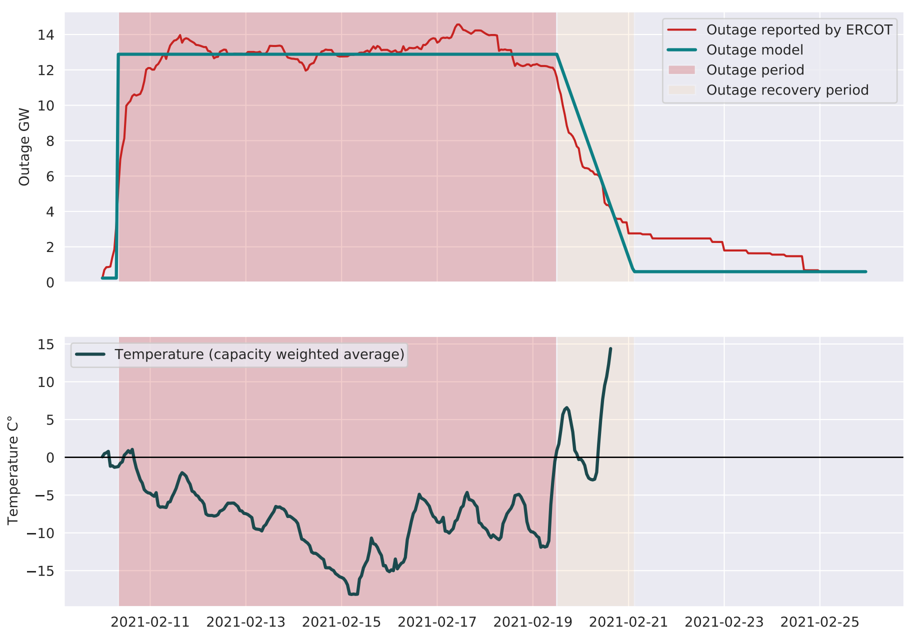

Figure A.9: **North wind outage approximation** Wind outages and temperature at wind power plants in Northern Texas and approximated outage model

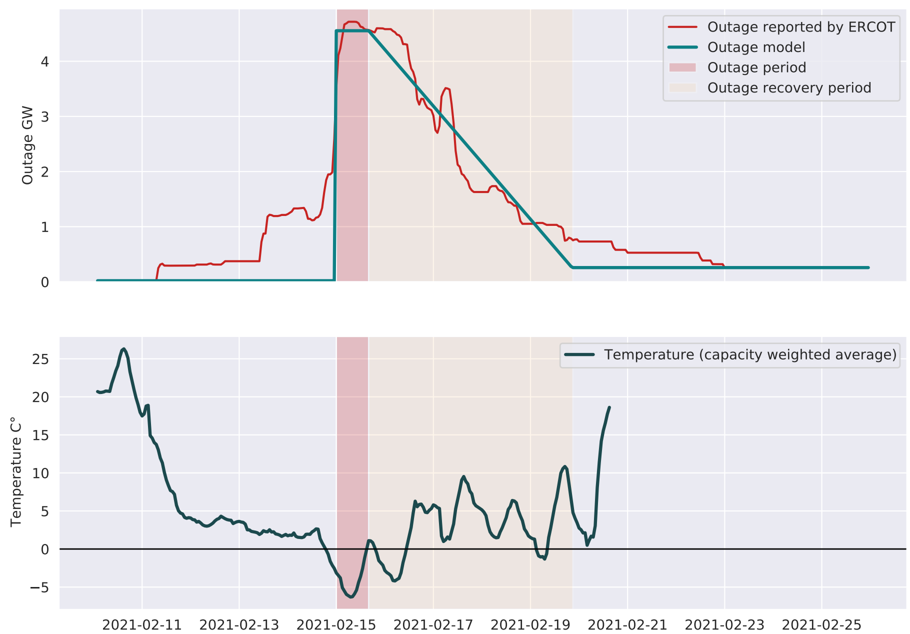

Figure A.10: **South wind outage approximation** Wind outages and temperature at wind power plants in Southern Texas and approximated outage model

A.6 Scarcity prices

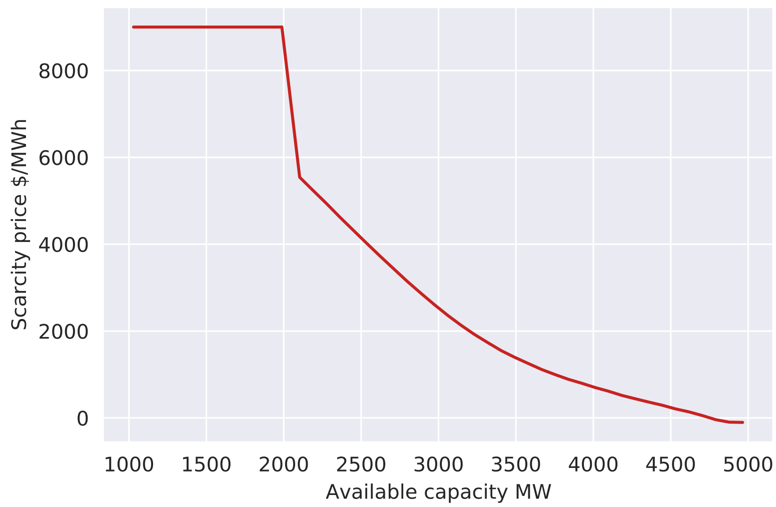

Figure A.11: **Scarcity prices** as regulated by ERCOT [32]. The less available capacity in the system, the higher the price at the energy only market

A.7 Trends in extreme events

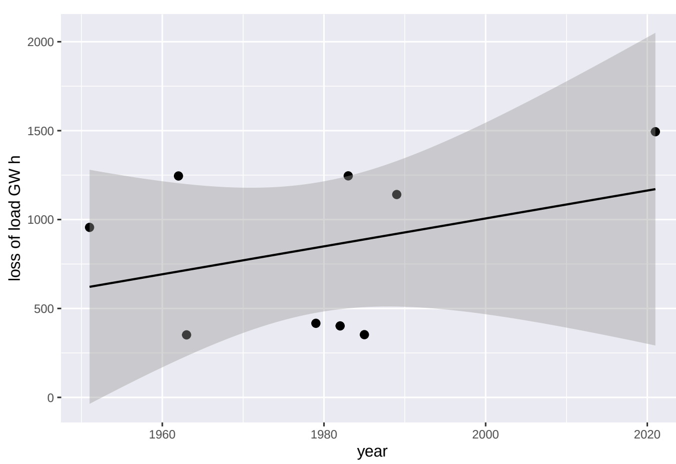

Figure A.12: **Trend in loss of load events** Loss of load events in the period 1950–2021 with non-significant trend line (p-value=0.31)

A.8 Modeling climate change trends in temperature

Figure A.13 shows mean yearly population weighted temperatures over the past 71 years. Regression indicates a clear trend towards higher average temperatures with an annual increase of 0.017°C.

In order to introduce an artificial linear trend to past temperatures, we increased all past temperatures by the trend observed in average temperature since 1950 assuming the linear trend of average temperatures would also translate to extreme temperatures, although there is no evidence of this phenomenon. Using the estimated average temperature trend of 0.017°C per year in the period 1950–2020, temperatures in the time series are updated in the following way:

$$t_{y,h}^{\text{trend}} = t_{y,h} + 0.017(y_{\text{ref}} - y)$$

We calculated two scenarios, using 2021 and 2050 as y_{ref}. These are the boundaries for our analysis, when considering a 30 years investment period.

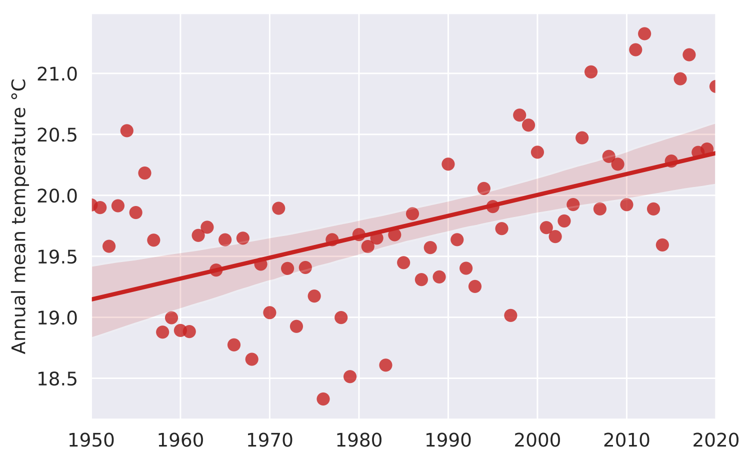

Figure A.13: **Temperature trend** Trends in population weighted annual mean temperatures

A.9 Trends in extreme temperature

The predicted outage relies on the stationarity assumption for the temperature time series, in particular on the assumption that there is no trend in temperatures. We use past climate data to simulate outages. Due to climate change, we however observe an increase in average temperatures in Texas. Our estimates may therefore be biased. Still, extreme events in the power system, in our model, occur at extremely low temperatures for the Texan context. These extreme freeze events do not necessarily follow the trend in the average increase of temperatures [10]. Our model uses a minimum threshold of -10.2 °C for coal, -8.8 °C for gas, -10.9 for gasfields, -1.2 °C for wind in Northern Texas and -3.1 °C for wind outages in Southern Texas. Therefore, we specifically need to examine stationarity of annual minimum temperatures below this threshold. By conducting a robust trend analysis for annual temperature minima below the threshold for different temperature thresholds, we find that extreme freeze events in Texas only show a trend if the temperature threshold is set to -1°C or above, i.e. very high. For temperature thresholds below -1°C, no trend can be confirmed (see Table A.2). Assuming a trend in a reduction of extreme freeze events below -1°C can therefore not be confirmed by the 71 years of temperature data available to us.

Table A.2: **Trends in cold temperature** with different temperature thresholds

Temperature threshold °C	Events	Slope yearly °C/yr	Slope 71 years	p-value
0	71	0.037	2.65	0.029
-1	70	0.037	2.61	0.033
-2	63	0.020	1.43	0.256
-3	55	0.004	0.30	0.816
-4	38	-0.005	-0.38	0.810
-5	30	-0.002	-0.11	0.948
-6	25	0.013	0.95	0.547
-7	20	0.018	1.27	0.474
-8	10	-0.028	-1.96	0.316
-9	8	-0.017	-1.22	0.422
-10	5	-0.013	-0.89	0.491

A.10 Calculation of winterization costs

There is very limited information on winterization costs available, and the information mostly comes from media reports. For gas wells, costs of 50,000$ for winterization are reported [26]. Winterizing all 123,000 gas wells in Texas [33] would therefore yield a total cost of 6.15bn$. 18GW of gas power capacity failed during the 2021 event according to our simulation. Conservatively assuming that winterization costs of gas fields can be split according to failed gas power capacity, winterization costs for gas fields of 342 Mio$/GW of gas power plant capacity can be derived. This is equivalent to around 250GWh of pipe storage for methane, which could be installed on the site of gas power plants to secure supply under cold conditions as alternative [34]. Busby et al. [5] estimate even lower costs at 50,000$ to 500,000$ per gas power plant - and they estimate that only 6% of all wells have to be winterized, as they produce the lion share of gas in Texas, lowering winterization cost drastically. Assuming costs of gas power plant winterization to be 10% of investment costs, total winterization costs result in 453 Mio$/GW of gas power capacity at an investment costs for gas power plants of 1.12bn$/GW [35].

For coal and wind power plants, no large-scale fuel supply infrastructure has to be winterized. Therefore, winterization cost will be significantly lower than for gas. Winterization of wind turbines is about 5% [11] of investment costs. Assuming investment costs of 1.3bn$/GW [36], this yields 65 Mio$/GW of wind power capacity as estimate of winterization costs for wind turbines.

For coal power plants, we did not find any estimate, and assume 10% of investment costs. At investment costs for coal power plants of 2.24 bn\$/GW [35], winterization costs of 224 Mio\$/GW are obtained.