**Measuring power outage exposure with simulations**

**Introduction:**

Power outage incidence is increasing[[1]](#endnote-1),[[2]](#endnote-2). Climate change has increased the frequency and intensity of extreme weather, such as heat, wind and precipitation[[3]](#endnote-3),[[4]](#endnote-4),[[5]](#endnote-5). Grid components have not been modernized to withstand these previously rare severe weather events [[6]](#endnote-6),[[7]](#endnote-7),[[8]](#endnote-8). As a result, US electrical customers experienced an average of 8 hours without power in 2020, the longest duration on record[[9]](#endnote-9).

Power outages pose serious health risks to vulnerable people. For those who use electricity-dependent medical equipment such as at-home ventilators and oxygen tanks, loss of electricity can be life-threatening[[10]](#endnote-10). In children, outages increase accidents and injuries related to generator and natural gas use[[11]](#endnote-11),[[12]](#endnote-12). Power outages can render air conditioners, heaters, and tap water unavailable, resulting in heat exposure, cold exposure, and dehydration in affected populations. Older adults are susceptible to stroke, myocardial infarction, and other adverse cardiorespiratory outcomes from such exposures[[13]](#endnote-13),[[14]](#endnote-14),[[15]](#endnote-15),[[16]](#endnote-16).

Despite the health risks of power outages, data describing power outage exposure is extremely limited[[17]](#endnote-17),[[18]](#endnote-18), constraining research. Only one US-based dataset describes outage exposure across space and time[[19]](#endnote-19) at a sub-county scale, and it is restricted to New York State. Most studies of power outages rely on this single dataset[[20]](#endnote-20). The remaining studies use large-scale events such as hurricanes or disasters which disrupted power as a surrogate for power outage exposure[[21]](#endnote-21),[[22]](#endnote-22). These studies consider everyone in a city or county exposed to the large-scale event as exposed to power outage in hours, days, or weeks following the event. Unfortunately, studies based on single events cannot disentangle the health effects of power outage exposure from simultaneous disaster exposure and they cannot be used to estimate exposure-response relationships between power outages and health.

Quantifying the health risks and costs associated with power outages can influence energy policy decisions. If power outages cause significant morbidity and mortality, improving grid infrastructure, community solar power, electricity storage, and electricity reliability may better community health. Knowing the health risks of power outages can also motivate intervention in vulnerable populations to prevent adverse health outcomes and mortality from outage.

In our previous work, we created a new national dataset of hourly power outage exposure for all counties in the continental United States[[23]](#endnote-23) (the PowerOutages.us dataset, or POUS dataset). This dataset will allow us to characterize exposure-response relationships between power outage and health outcomes nationally, by region, and within vulnerable populations. However, even with these new data, major challenges with power outage exposure assessment remain.

First, there is no established strategy to measure a health-relevant power outage exposure in the literature[[24]](#endnote-24). A single strategy to describe power outage exposure would allow comparability and aggregation of results across studies.

Second, the health-relevant duration of power outage matters for exposure assessment. However, there is no literature describing how long power outages must be to cause any health outcome. There are likely threshold effects where power outages longer than some duration cause adverse health outcomes, but shorter outages do not. For example, 8+ hour power outages may affect the health of those using oxygen tanks and at-home ventilators, when after 8 hours of power outage, device batteries with an 8-hour life die. Shorter outages may have no effect. Incorrect assumptions about the health-relevant duration have the potential to bias the results of epidemiological studies of power outage and health outcomes.

Finally, both the New York State and POUS datasets are missing large percentages of observations[[25]](#endnote-25),[[26]](#endnote-26), with some counties in POUS missing up to 70% of county-hours. In the POUS dataset, data are missing if utilities did not have a website, or if utility websites were offline or unscrapable for long periods of time (months or years). In these cases, interpolating missing values is nearly impossible because no data exists from which to extrapolate. To reduce bias, researchers could exclude counties that are missing more than a specified percentage of observations from epidemiological studies, but removing too much data could threaten the generalizability of effect estimates from these studies.

In this paper, we addressed these exposure measurement issues. First, we developed a strategy for measuring power outage exposure. Then, we ran simulations to address the two other potential sources of bias: incorrect assumptions about health-relevant duration, and bias from missing data. First, we quantified the magnitude and direction of bias introduced when researchers assumed one length of power outage (for example, 8+ hour outages) caused health outcomes, but outages of a different length (for example, 4+ hour outages) actually caused health effects. Second, to deal with missing data, we used simulations to identify a percentage threshold, where if a county is missing more than that threshold, the missing data begins to severely bias effect estimates and researchers should exclude counties missing more data than this threshold.

Our results contribute to the exposure literature with a proposal for consistently defining and measuring power outage exposure using the datasets currently available, while minimizing potential bias in future epidemiological studies of power outages and health outcomes.

**Methods:**

**Power outage data structure**

In our previous work, we created a national county-level hourly dataset of power outage exposure[[27]](#endnote-27). We purchased raw power outage data from PowerOutages.us. Most utility websites report the number of customers without power by neighbourhood or city in real-time, so customers can track outages. To create this dataset, PowerOutages.us scraped counts of customers without power from utility website APIs covering the continental US, in real-time, every hour from 2018–2020[[28]](#endnote-28).

The resulting dataset contained hourly counts of customers without power for each US county from January 1st, 2018, to December 31st, 2020. Utilities define a ‘customer’ as a grid connection, which can correspond to a household, apartment building, or business[[29]](#endnote-29). Counts of customers out reported in this dataset do not necessarily track the same customers: if 10 customers are reported without power in two subsequent hours in one county, the data do not contain information about whether the same 10 households lacked power. The data only show the total count of households without power each hour.

The New York State power outage dataset is structured similarly – counts of customers without power are reported by hour by power operating division[[30]](#endnote-30),[[31]](#endnote-31). Power operating divisions are geographic units varying in size but similar to ZIP codes throughout the state.

**Strategy to measure power outage**

To measure daily binary power outage exposure in the POUS dataset and New York State dataset, we propose the following strategy. We implement the strategy in the POUS data, as an example.

Since the health-relevant duration of power outage may change depending on the health outcome studied, we suggest a flexible definition of power outage exposure to identify power outages of varying lengths. Although continuous measures of power outage are possible, we estimated daily binary exposure because binary metrics are easily interpretable by policymakers and non-scientists. In particular, we think that a binary measure of power outage will allow for clear communication about the health risks of power outages. We also hypothesize that power outages will not have health effects until they reach a certain duration. A binary definition of power outage exposure models these threshold effects. The measurement strategy we propose here is also similar to previous definitions of power outage exposure used in the literature[[32]](#endnote-32),[[33]](#endnote-33),.

To determine if a county-day was exposed to power outage, first we considered each hour alone. We considered a county-hour exposed to power outage if the percentage of customers without power in county *i* during hour *j* exceeded an arbitrary cut point *k* – for example, 10% of the customers. If more than 10% of customers served in county *i* were without power in hour *j*, there was a power outage in county *i* during hour *j*.

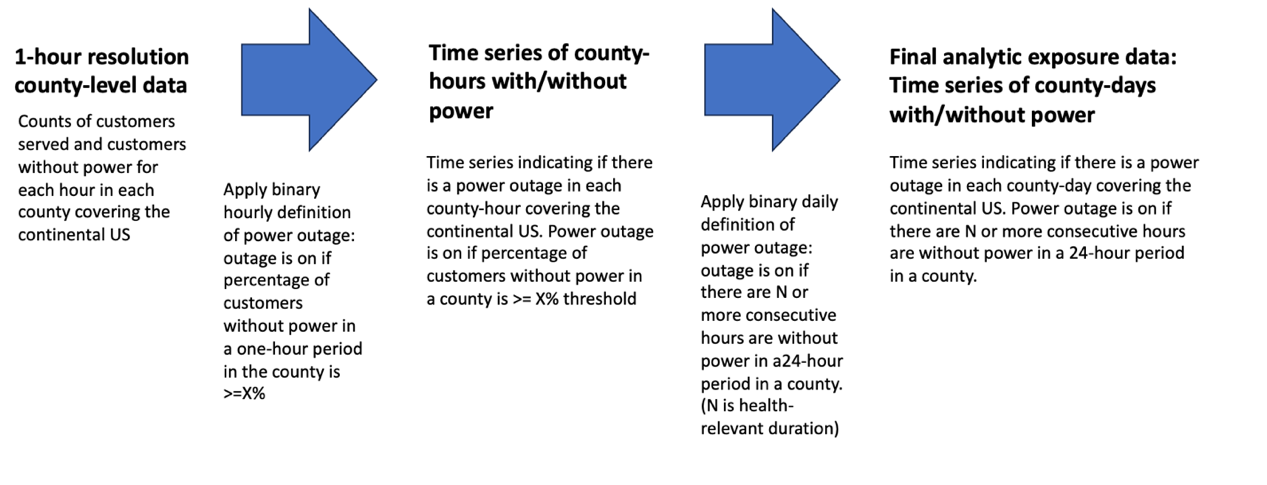
We then summarized this hourly exposure to the daily level. We chose a health-relevant duration *l* (for example, *l* = 8 hours); this could be any duration selected by a researcher. We considered a county-day as exposed if there were at least 8 consecutive hours of ‘power outage on’ (customers without power percentages > *k*% of county) in that county on that day, or ending on that day.

When a county is exposed to an 8+ hour power outage according to this definition, this does not mean that there will be 10% of people in that county without power for at least 8 hours that day, since one customer could represent many people, and individual customers are not tracked over time. Instead, an 8+ hour outage indicates that many individuals were likely without power for close to 8 hours in that county on that day; this definition describes spatial-unit level exposure rather than an individual exposure.

Relatedly, there is exposure misclassification inherent in this definition: when the county is ‘exposed’, some customers in the county will be without electricity and others will still have electricity. Other studies of power outage exposure using a similar exposure definition have dealt with this exposure misclassification by conducting sensitivity analyses varying the cut point after which a unit is considered exposed to power outage. For example, Northrop et al. considered a spatial unit exposed to power outage if more than 10% of the customers served in that unit were without power, and conducted two sensitivity analyses where they considered a spatial unit exposed to power outage if more than 20% and 30% of the customers served in that unit were without power[[34]](#endnote-34). As the cut point percentage increases, the specificity of this definition of power outage increases.

We propose using this strategy for measuring power outage exposure, while always conducting a sensitivity analysis on the cut point.

Here's a draft of a flowchart that might help keep this on the rails in the future?



**Simulation design**

**Overview**

We designed a simulation representing an epidemiological study measuring the association between power outage exposure and hospitalization rates. This study was meant to mimic a study that could be conducted using the POUS data. The outcome of ‘hospitalizations’ is intentionally vague and could be any health outcome hypothesized to be exacerbated by power outages. We simulated daily binary power outage exposure for 100 US counties for one year and daily county-level hospitalization rates for these counties for the same period. We generated effect estimates of power outage exposure on hospitalization in an unbiased scenario, and then in scenarios representing incorrect assumptions about the health-relevant power outage exposure duration and including missing data. We conducted all simulations twice using two different study designs, to test the sensitivity of results to study design.

**Exposure and outcome data**

We generated one year of county-hour power outage exposure data for 100 simulated counties. We populated each county with electrical customers, drawn from the empirical distribution of customers served by county in the POUS dataset. To generate hourly counts of customers without power, we drew from the empirical distribution of counts of customers without power in the POUS dataset.

We chose the health-relevant duration of power outage for our study: 8 hours or longer (8+ hours). This was somewhat arbitrary – in a real study, the health-relevant duration would depend on the actual outcome being studied and how power outages were thought to affect that outcome. However, in reality, we do hypothesize that 8+ hour power outages matter for electricity-dependent medical device users, as well heat and cold-related outcomes caused by outage, so we chose to use 8+ hours in the simulation. We applied our definition of power outage exposure to the simulated exposure data and identified county-days exposed to 8+ hour power outage. This produced a one-year daily time-series of binary power outage exposure data for each county.

We generated outcome data based on this exposure data. We drew hospitalization counts for each county-day based on a Poisson distribution with a base hospitalization rate of 0.1%. We increased this hospitalization rate for county-days exposed to 8+ hour outage by 1%, for a total hospitalization rate of 0.101%. This produced one-year time series of daily hospitalization rates for each county. We repeated this procedure twice more, increasing hospitalization rates on exposed days with effect sizes of 0.5% and 5%, to test the sensitivity of results to effect size.

**Simulation study design**

First, we used a base case/unbiased scenario to estimate the true simulated effect of county-day 8+ hour power outage exposure on county-level hospitalization counts. We used a case-crossover design with a conditional quasi-Poisson model[[35]](#endnote-35). Within each county, we chose control days for each day with non-zero hospitalization count (each case day). We included these case and control days in a quasi-Poisson model relating power outage exposure to hospitalization rates. In this model, we included an offset for customers served by county, and a fixed effect for county. We repeated this simulation, including exposure data creation, outcome data creation, and modeling 100 times, and for effect sizes of 0.5% and 5%.

We also repeated the simulation using a different study design, which we used to test if the simulation results were sensitive to study design. We implemented a simplified difference-in-differences design. We used the same exposure and outcome data generated for the case-crossover simulation. For each day exposed to power outage, we chose a control day not exposed to power outage from another county. We ran a Poisson model including all these case and control days from all 100 counties. We used exposure and outcome data created 100 times for the case-crossover design to repeat the difference-in-differences analysis 100 times, and for effect sizes of 0.5% and 5%.

**Testing wrong assumptions about health relevant duration:**

We created a simulation meant to model a researcher making wrong assumptions about the health-relevant duration of power outage. We assessed the magnitude and direction of the resulting bias. This simulation models a case where the researcher assumed 8+ hour outages caused health effects, but it was actually 4+ hour outages caused health effects.

To model this scenario, first, we created an additional power outage exposure dataset for each simulated county. Using the measurement strategy above, we identified county-days exposed to 4+ hour power outages instead of 8+ hour outages. We generated an additional dataset of outcome data, increasing hospitalization rates when counties were exposed to 4+ hour outages. We used the same hospitalization rate of 0.1%, with a 1% rate increase on power outage exposed days. Then, we mismatched the exposure and outcome data: we paired exposure data indicating when counties were exposed to 8+ hour power outages with outcome data generated based on 4+ hour outages.

We repeated the study we conducted above in the base case/unbiased scenario, using the mismatched datasets. We used a case-crossover design with conditional quasi-Poisson models. We chose control days for each day with non-zero hospitalization count. We ran quasi-Poisson models to generate effect estimates for the mismatched scenario. We repeated this simulation 100 times.

We also repeated this simulation an additional 100 times, substituting 12+ hour power outages for 4+ hour power outages, and for effect sizes of 0.5% and 5%.

We also repeated the 4+ and 12+ hour simulations using a difference-in-differences design to test whether results were sensitive to the study design. Again, for each day exposed to power outage, we chose a control day not exposed to power outage from another county. We used those case and control days in a Poisson model to generate effect estimates for each of the two mismatched scenarios (4+ and 12+ power outages), and repeated the analysis again for effect sizes of 0.5% and 5%.

We calculated bias in all these simulations, using the absolute difference between the estimated effects and simulated effects (*𝛽*ˆ−*𝛽*; *𝛽*ˆ is the estimated effect and *𝛽* is the simulated effect) (Table 1, and Figure 1). We also assessed coverage of confidence intervals in each of the simulations.

**Testing bias from missing data:**

To test bias from missing exposure data, we created four additional exposure datasets for each of the 100 simulated counties, each with an increasing percentage of missing observations (10%, 30%, 50%, 70%). To create missingness, we randomly removed county-hour observations from the original dataset until the correct percentage of observations were omitted. We treated missing observations as though they indicated no power outage exposure (0 customers without power) since this is the mean, median, and modal value of customers without power by county-hour in the POUS dataset. We applied our definition of power outage exposure to these four datasets with missingness to create daily binary power outage exposure data based on a power outage duration of 8+ hours.

We then modeled the relationship between 8+ hour power outage exposure measured in each of the four datasets with missing data (10% - 70% missing data) and all-cause hospitalization counts generated based on an 8+ hour power outage exposure in the complete dataset with no missingness. We used the case-crossover study design and a difference-in-differences design as above. We repeated the simulations 100 times, and for effect sizes of 0.5% and 5%.

We calculated bias in each of the four cases with increasing missingness again using the absolute difference between the estimated effects and simulated effects (*𝛽*ˆ−*𝛽*; *𝛽*ˆ is the estimated effect and *𝛽* is the simulated effect) in each of the 100 models for each case using the case-crossover study design and difference-in-differences design, and for effect sizes of 0.5% and 5% (Figure 1). We also assessed coverage of confidence intervals.

**Results:**

**Bias:**

* We found evidence of some bias in our simulations, modelling incorrect assumptions about health-relevant duration of power outage, and missing data.
* In the unbiased simulation scenario, results were indeed unbiased. In all cases where exposure misclassification or missing data were introduced, on average, results were biased towards the null. The largest bias was introduced from wrong assumptions about health-relevant duration. There was also substantial bias when 50%-70% of data were missing. Other cases were minimally biased.
* In models representing a researcher making wrong assumptions about the health-relevant duration of power outage, when the simulated health-relevant duration of outage was shorter than the duration assumed by the researcher, results were slightly biased towards the null. This was modelled in the case where 4+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects. In this case, the effect estimates returned from the simulation were on average 20% smaller than the simulated risk. The magnitude of bias was not different between effect size or study design.
* When the simulated health-relevant duration of outage was longer than the duration assumed by the researcher, results were substantially biased downward. This was modelled in the case where 12+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects. In this case, effect estimates were on average 50% of the true simulated effect. The magnitude of bias was not different between effect size or study design.
* In missing data cases, as more missing data was introduced, results were biased further towards the null. At 50% of data missing, effect estimates returned from the simulation were around 25% of the true simulated effect estimates. When 70% of data were missing, effect estimates were 50% of the true simulated effect. Results were not sensitive to study design or effect size.

**Coverage:**

* In the unbiased base case scenario, 95% confidence interval coverage was close to 95%, as expected.
* In health relevant duration exposure misclassification scenarios, coverage was high (close to 95%) when effect size was small, since confidence intervals were large, but dropped significantly as effect size increased, which in turn increased precision.
* In models representing a researcher making wrong assumptions about the health-relevant duration of power outage, in the case where 4+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects, coverage for models where the simulated effect size was 5% was close to 65%. When 12+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects, coverage for models where the simulated effect size was 5% was close to 0, since effect estimates were both biased and precise.
* In scenarios with missing data, coverage was high when effect sizes were small, but again dropped significantly as effect size increased and as the proportion of missing data increased. When effect size was 5%, even when 10% of data were missing and results were on average minimally biased, coverage was about 30%. Coverage was about 0% when 50% or 70% of data were missing and effect size was 5%.
* Overall, in all cases, coverage was slightly less when using a case-crossover design, since results from this design were slightly more precise.

**Discussion:**

**For discussion from above:**

Summarize results:

* In simulations where we modeled incorrect assumptions about the health-relevant duration of power outage, and exposure data missing substantial percentages of observations, we found evidence of bias. The magnitude of bias varied between simulation cases.
* Of all simulations cases, results were the most biased when researchers assumed the health-relevant duration of power outages was shorter (8+ hour power outages) than the actual simulated health relevant duration (12+hours). However, when the assumed health-relevant duration of outages was longer (8+ hours) than the true health-relevant duration (4+ hours), there was minimal bias.
* When large proportions of exposure data were missing (50-70% missing), there was substantial bias, but results were mostly accurate in scenarios where there was less missing data (30-50% missing).
* The magnitude of bias did not depend on study design or effect size. However, coverage was low in cases where the effect estimates were substantially biased and the simulated effect of power outages on health was stronger, at 5% rather than 1% or 0.05%.

Contextualize the results:

* Some studies have used similar definition of power outage exposure to the one we propose here, such as Northrop et al.
* Our results suggest that those effect estimates may be subject to bias from the sources we examined here
* Could be that if 4 hr power outages were causing effects could be biased slightly downward or something (give example of study done by our group), or could be biased even more downward from 12+ hour.
* If the dataset used in that study was missing substantial data, then effect estimates may have been biased towards the null.
* Currently, power outage is an understudied exposure, but researchers and the public are begniing to recognize the importance of power reliability and the potential health consequnces of outages, especially when the coocurr with severe weather. Few studies examine power outage and health outcomes.
* However, as climate change progresses and extreme weather events become more common, people are beginning to recognize the importance of power outage exposure and power reliability to health
* Data availability has constrained research
* Our dataset could be a super important dataset that would allow people to study power outage exposure, but we were concerned that the missing data and lack of knowledge about health-relevant duration could be big problems.
* Our results shows that this dataset is still good to use for research
* May want to exclude counties that are missing more than 50% of data, to reduce bias from missing data.
* But still possible to use data from places with minimal missing data.
* Cannot completely exclude the possibility of bias, but it appears bias is not detrimental
* Issues that we thought are really terrible and not as bad as we though

Recommendations for other researchers:

* When other people use this dataset and when in general people use datasets to measure power outage
* And they use this definition of power outage exposure
* When they do duration they should maybe conduct sensitivity
* Missingness results might only apply to this dataset - depends if missingness is still bad
* Although we have a lot fo missing data in this dataset and coverage issues, compared to other measurement procedures, we still have a lot of measurements. We have data for every hour for most of the country. This dataset is pretty useful.

Limitations:

* We only assessed non differential missingness
* It could be that in this dataset and in other datasets missingness could be differential
* Could cause a lot more bias than what we saw here
* Missingness might also affect generalizability of effect estimates even if it doesn’t bias the effect estimates that we’re getting
* Also didn’t look at individual vs spatial unit
* Different paper and future research direction

This definition of power outage exposure allows us to specify a health-relevant duration of power outage for the health outcome of interest. It allows us to compare spatial units with different populations of customers served. It is also readily interpretable by policy makers. Exposure misclassification is inherent in a daily binary definition of power outage exposure, and this exposure measurement strategy allows us to conduct a sensitivity analysis by varying the cut-point used.

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