**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 (Figure 1).

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.

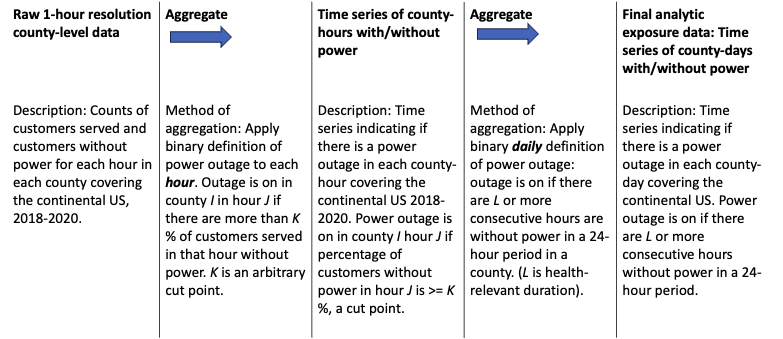


Figure 1: Flowchart describing how the proposed definition of power outage exposure could be applied to the PowerOutages.us data. The raw PowerOutages.us data contains county-level hourly counts of customers without power for all counties in the continental US, 2018-2020, and could be aggregated into daily binary indicators of power outage according to the strategy proposed in the text and outlined in this flowchart. Feedback appreciated!

**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. This created exposure misclassification where we used 8+ hour exposure data rather than 4+ hour exposure data.

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%. This created an additional scenario, where we had exposure misclassification due to using 8+ hour power outage exposure data rather than 12+ hour data.

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 2). We also assessed coverage of confidence intervals in each of the simulations (Figure 3).

**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% (Table 1, Figure 2). We also assessed coverage of confidence intervals (Figure 3).

**Results:**

**Bias:**

* We found some evidence of bias in these simulations representing an epidemiological study of power outage and hospitalizations, in cases modelling exposure misclassification and missing data.
* On average, results from these cases were biased downward.
* In the simulation cases representing a researcher making wrong assumptions about the health-relevant duration of power outage, when the health-relevant duration of power outage assumed by the researcher (8+ hours) was shorter than the true simulated health-relevant duration (12+ hours), results were substantially biased downward.
* In this case, the effect estimates returned from the simulation were on average 50% smaller than the true simulated relative risk – the largest bias of all the simulation cases. The magnitude of bias was the same for all effect sizes and study designs.
* However, when the health-relevant duration of outage assumed by the researcher (8+ hours) was *longer* than the true simulated duration (4+ hours), results were slightly biased downward.
* In this case, effect estimates returned by the simulation were on average 80% of the true simulated relative risk. Again, magnitude of bias was the same for all effect sizes and study designs.
* In simulation cases where missing data were introduced, as more data were missing, the relative risk returned from simulations was biased further towards the null.
* At 10% of data missing, effect estimates returned from the simulation were 90% of the true simulated relative risk.
* When 50% of data were missing, effect estimates returned from the simulation were 75% of the true simulated relative risk, and when 70% of data were missing, effect estimates were 50% of the true simulated effect.
* The magnitude of bias was not sensitive to study design or effect size.
* To summarize, the largest bias was introduced from wrong assumptions about health-relevant duration of power outage. There was also substantial bias when 50%-70% of data were missing. Other simulation cases were minimally biased (Table 1, Figure 2).

**Coverage:**

* In scenarios modelling incorrect assumptions about health relevant duration, coverage varied widely by effect size, and was different between the two exposure misclassification scenarios.
* In the simulation 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 with simulated effect size 0.05% was close to 100, because bias was minimal and effect estimates imprecise.
* For effect size of 5%, coverage was close to 65%. Coverage was lower because of increased precision.
* In the second health-relevant duration simulation, 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 with simulated effect size 0.05% was close to 80%.
* Even though these effect estimates were biased, they were imprecise due to the tiny effect size, leading to higher coverage.
* However, for the effect size of 5%, coverage was 0%, since effect estimates were both substantially biased and precise.
* In scenarios with missing data, coverage was high when effect sizes were small, even if there were large amounts of missing data.
* When 10% of data were missing and the effect size was 0.05%, coverage was >95%, due to effect estimate imprecision.
* Coverage dropped substantially in all cases as effect size increased, due to the increased precision of results. When 10% of data were missing and effect size was 5%, even though results were minimally biased, coverage was about 30%.
* Coverage in missing data scenarios also decreased as the proportion of missing data increased, due increased bias in effect estimates.
* Coverage was about 0% when 50% or 70% of data were missing and effect size was 5%.
* Overall, in exposure misclassification scenarios and missing data scenarios, coverage was slightly less when using a case-crossover design, since results from this design were slightly more precise.

**Discussion:**

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.
* 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 results were more precise due to the higher effect size of 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 the effect estimates in Northrop et al. (of the effect of power outages on pediatric unintentional injury hospitalizations) may be subject to bias from the sources we examined here.
* Northrop et al. assumed that the health-relevant duration or power outage for unintentional pediatric injury hospitalizations was 4+ hours. If longer duration outages were actually more relevant, effect estimates in Northrop et al could be biased substantially downward. If slightly shorter outages were actually relevant, which could be possible since injuries might be related to darkness or increased natural gas use, results could be slightly biased downward.
* If spatial units in the New York State dataset used in that study were missing substantial data, then effect estimates may have been biased towards the null from that missingness.

Advice for other researchers:

* In future studies, we can use the simulation results to protect against bias from these sources.
* Our results show that excluding spatial units with >50% missing data could help reduce bias in any future studies using power outage data, as effect estimates from simulations with less missing data were only slightly biased, whereas the magnitude of the bias increased substantially after 50% of observations were removed from the dataset.
* Getting the health relevant duration correct is key, and there’s little information about that.
* Important to either conduct a sensitivity analysis if you think the health relevant duration could be longer than the study specifies, or conduct analyses multiple times using different durations, or use continuous measures of power outage such as tallying the number of hours without power in a day and using that if it makes sense in your study.

Our study shows that these data are usable:

* Currently, power outage is an understudied exposure, but researchers and the public are beginning to recognize the importance of power reliability and health consequences of outages. Especially when they are caused by severe weather such as extreme heat or cyclones which is more bc climate change.
* To date, data availability has constrained research on power outages and health.
* The dataset we have created could allow people to study power outage exposure, but we were concerned that missing data and health-relevant duration might bias results of studies using this dataset.
* Our results show that while these factors have the potential to bias results, that it is possible to mitigate these biasing effects.
* Although the POUS dataset does contain a lot of missing data, and it may seem like there are coverage issues, we still have a lot of measurements and compared to measuring something like once a year, this is good.
* 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
* To deal with missingness, we’ve proposed excluding certain spatial units. If there’s a region with a lot of missing units, could threaten generalizability of results to the whole US.
* In this study we didn’t assess how aggregating measurements from the individual level to spatial unit level would affect effect estimates. Power outage is an individual binary exposure, and we’ve measured it at the county level. This is an important question since all data available right now are aggregated.

**Conclusion:**

* we had a new dataset of power outage exposure
* we were worried how to define power outage exposure well, and if wrong assumptions about health-relevant duration of exposure and missingness could bias results of studies of outage and health
* we proposed a definition for measuring power outage, and assessed bias from these sources of concern in simulations
* we found that there was substantial bias introduced in some cases, when there was a lot of missing data, and when the health-relevant duration of outage was assumed to be shorter than was true
* though there was bias, we think that by conducting sensitivity analyses on health relevant duration and excluding spatial units with a lot of missing data, this dataset is still very useful for investigating the effects of power outage on health at a national level
* we will use it to do that and hope others will too.

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