Equitably Allocating Wildfire Resilience Investments for Power Grids – The Curse of Aggregation and Vulnerability Indices

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April 18, 2024

Abstract

Wildfires ignited by power systems infrastructure are among the most destructive wildfires; hence some utility companies in wildfire-prone regions have pursued a proactive policy of emergency power shutoffs. These shutoffs, while mitigating the risk of disastrous ignition events, result in power outages that could negatively impacts vulnerable communities. In this paper, we consider how to equitably allocate funds to underground and effectively de-risk power lines in transmission networks. We explore the impact of the 2021 White House resource allocation policy called the Justice40 initiative, which states that 40% of the benefits of federally-funded climate-related investments should go to socially vulnerable communities. The definition of what constitutes a "vulnerable" community varies by organization, and we consider two major recently proposed vulnerability indices: the Justice40 index created under the 2021 White House and the Social Vulnerability Index (SVI) developed by the Center for Disease Control and Prevention (CDC). We show that allocating budget according to these two indices fails to reduce power outages for indigenous communities and those subject to high wildfire ignition risk using a high-fidelity synthetic power grid dataset that matches the key features of the Texas transmission system. We discuss how aggregation of communities and "one size fits all" vulnerability indices might be the reasons for the misalignment between the goals of vulnerability indices and their realized impact in this particular case study. We provide a method of achieving an equitable investment plan by adding group-level protections on percentage of load that is shed across each population group of interest.

The increased frequency and severity of wildfires across the United States in the 21st century necessitates policy and infrastructure change to mitigate property damage, environmental impacts, and loss of life from these extreme events [1]. While power line-sparked ignitions account for a small fraction of the total number of wildfires in the United States, the environmental conditions that can prompt power line faulting can lead to catastrophic burn rates and spread, making them more destructive than wildfire ignitions attributable to other causes [2]. Furthermore, climate change is increasing the risk of these ignitions. For example, recent wildfires like the Smokehouse Creek (Texas), Maui Morning Fire (the ignition sources of the larger Lahaina, Hawaii fires are contested), Echo Mountain (Oregon), and Camp (California) fires have been linked to ignitions from power infrastructure [3]. To prevent such wildfires, high wildfire-risk states like California, Washington, and Oregon employ emergency public safety power shutoff (PSPS) events, in which power lines are proactively de-energized during high wildfire-risk[1] conditions. Some utility companies turn off power

[1]Risk is determined by a combination of environmental factors (e.g., heat, humidity, vegetation, and wind conditions) and line characteristics (e.g., voltage level, rating, routing, and condition) [4].

lines even in states where there *is not* a formalized process for planning a PSPS event, including recent emergency power shutoffs in Colorado, Kansas, Nebraska, and Oklahoma [5], demonstrating how valuable power shutoffs can be for mitigating wildfire ignition risks in high-wind conditions. When many power lines, or some few key ones, in a given region are de-energized, certain locations may experience power outages (referred to as *load shed*), where the amount of power supplied does not meet the amount of load demanded, and whole communities may lose power. Loss of power can have many negative effects on individuals and neighborhoods; however, certain groups are more negatively impacted by power outages than others [2][7, 8].

An alternative solution to power line de-energization is to bury or "underground" high-risk power lines. Undergrounding largely eliminates the possibility of a wildfire, and as a result, these lines never need to be de-energized due to wildfire concerns. Hence, the strategic undergrounding of high-risk power lines would eliminate the need for emergency power shutoffs. The main barrier towards implementing this solution is that undergrounding power lines in transmission networks is expensive, costing anywhere from \$5 to \$10 million per mile [9, 10]. While many major utility companies in high wildfire-risk regions have aggressive plans to underground power lines, the time horizons for these projects can expand over decades and cost tens of billions of dollars [11, 12]. Given the significant cost of undergrounding, this becomes an allocation problem under limited resources.

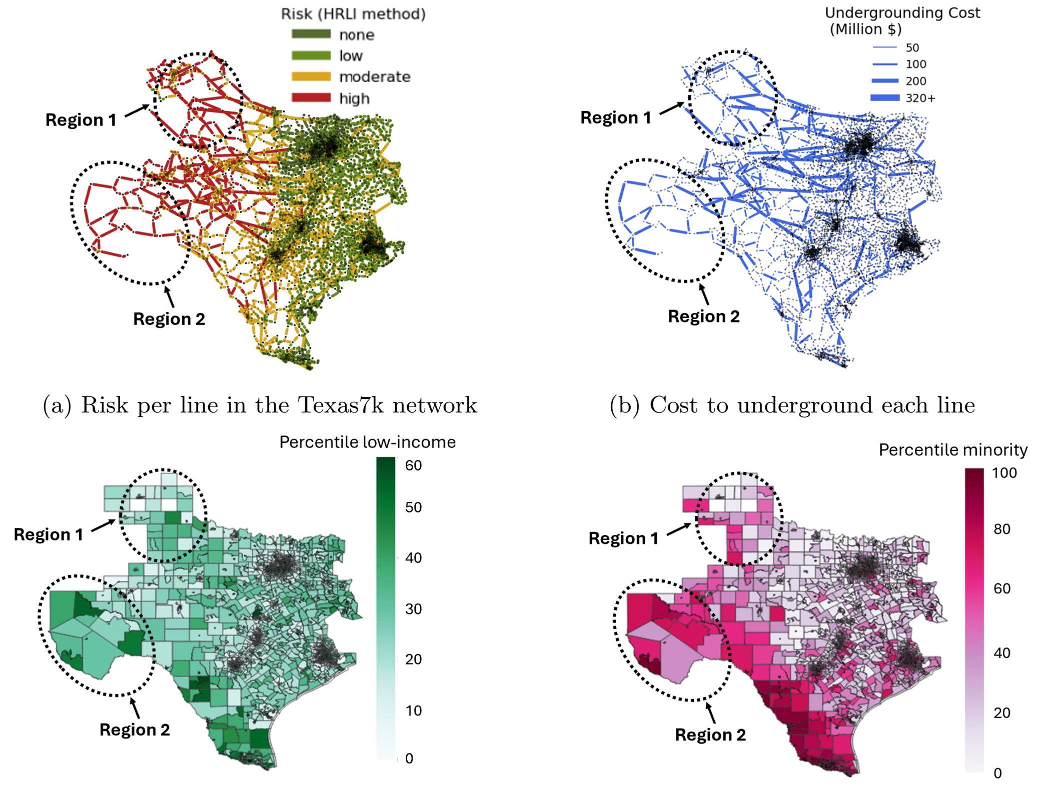
As with any resource allocation problem, being equitable with respect to different populations is a major concern. In particular, it is important to protect certain groups that have been historically underserved and subject to climate risk, while simultaneously ensuring that resources are being allocated to have maximum impact on overall wildfire risk reduction. To answer this broad question of how to equitably allocate infrastructure investment budgets, United States Executive Order 14008 [13] established the Justice40 initiative, which states that 40% of the benefits of federal investment in transportation, power, environmental, and other systems should flow to disadvantaged communities [14]. In fact, the Justice40 initiative has identified certain census tracts as vulnerable, broadly based on national percentiles of different types of climate risk (e.g., flood risk, agriculture loss rate, wildfire spread risk) coupled with low-income statistics[3]. There also exist other possible categorizations of vulnerability indices from other organizations, including the Center for Disease Control and Prevention's (CDC's) Social Vulnerability Index (SVI), which focuses on socioeconomic factors[4] [15]. Furthermore, these metrics are already being used in various domains for making equitable decisions including power systems [16, 17], healthcare [18, 19], and disaster relief [20, 21].

In this work, we focus on understanding efficient and equitable allocations of a given budget for mitigating high wildfire risk by either de-energizing or undergrounding high risk lines. In particular, we explore the proposed Justice40 allocation by using constraints that either ensure (i) 40% of the budget is spent on vulnerable census tracts as identified by Justice40 and SVI definitions, or (ii) budget is spent so that 40% of benefit in reducing load shed due to line de-energization goes to these designated census tracts. We refer to both of these

[2]Poorer families are less likely to own a backup power generator, so they are much more susceptible to food and medicine spoilage as well as loss of critical cooling in hot summer months if they lose power [6].

[3]Justice40 census tracts are generally defined by being at or above the 90th percentile of one of many climate risks (including wildfire risk, agriculture loss rate, projected flood risk, and others) as well as being above the 65th percentile for the fraction of households which are low-income (two times the federal poverty line) out of all households in the United States. Registered tribal lands are also automatically considered Justice40 areas, although indigenous communities living off-reservation are not included. See Appendix C.2 for more details

[4]The CDC's SVI metric considers a census tract as vulnerable if that tract is at or above the 75th percentile of one of four themes: socioeconomic status, household characteristics, racial/ethnic minority status, and housing type/transportation. See Appendix C.3 for more information



(a) Risk per line in the Texas7k network

(b) Cost to underground each line

(c) Percent of tract <$25k income

(d) Percent of tract that is racial minority

Figure 1: This figure shows some vulnerability characteristics of the synthetic Texas7k network where the circled regions show the overlap in vulnerabilities between these four metrics (wildfire risk, high cost to underground, low-income status, and racial minority status). We can see that the western and northern-most parts of Texas experience overlap in these different vulnerability characteristics, making these areas most susceptible to power outages from PSPS events (high wildfire risk, but lower ability to cope due to lower income) as well as lower likelihood of being selected for power line undergrounding due to lower population density (not pictured) and the high cost to underground the lines.

as Policy constraints. To understand the impacts of these Policy constraints, we use a high-fidelity synthetic power grid dataset that is validated to match key features of the Texas transmission system [22] along with actual wildfire ignition risk [23] and demographic data.[5] We explore the effectiveness of Policy constraints in minimizing the load shed across various demographic groups, while keeping the risk in the network below reasonable thresholds. We perform this analysis using a mixed-integer program (MIP) optimization model, the details of which can be found in the Methods section.

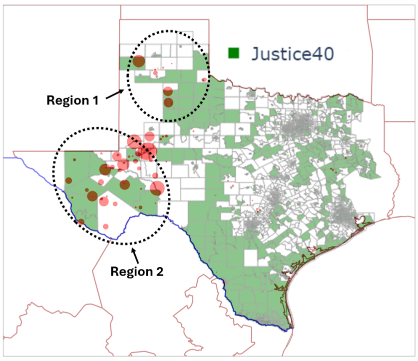
This analysis allows us to evaluate (i) the effectiveness of vulnerability indices (e.g., Justice40, SVI) in making specific climate investment decisions, and (ii) the resultant impact of these investments on historically burdened communities using the 6717-bus Texas Synthetic Grid.

Results

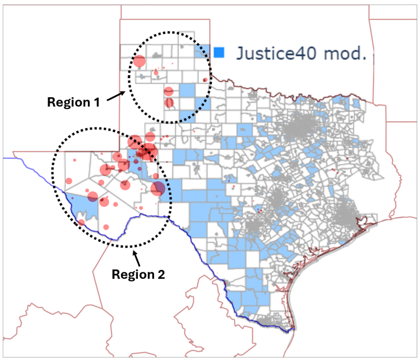
We find that by and large, generalized vulnerability indices are not necessarily suitable for describing disadvantage in specific contexts like vulnerability to wildfires or power outages; that is, climate vulnerability indices are not "one-size-fits-all" metrics. Furthermore, indige-

[5] Power systems are considered critical energy infrastructure information [24]. Given this security sensitivity, real power system information is typically classified to prevent any attacks. Synthetic networks provide a way to evaluate decisions on realistic models. See Appendix A.1.

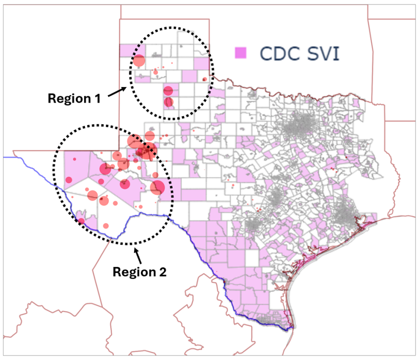
nous groups are unlikely to be categorized as “disadvantaged” under these indices, despite experiencing higher levels of poverty and higher exposure to wildfire risk, and are thus unlikely to receive the benefit of investments in power line undergrounding. We posit that the reasons for this may be the design of vulnerability indices and, what we call, the “curse of aggregation”, which we describe in more detail below.



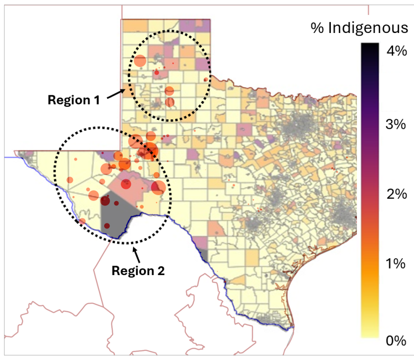
(a) Justice40 census tracts are depicted in green. Approximately 40% of all Texas census tracts are Justice40 tracts, and only 37% of Texas census tracts experiencing load shed are Justice40 tracts.



(b) Modified Justice40 census tracts are depicted in blue. Approximately 18% of all Texas census tracts are Modified Justice40 tracts, and only 22% of Texas census tracts experiencing load shed are Modified Justice40 tracts .



(c) The CDC’s SVI census tracts are depicted in pink. Approximately 38% of all Texas census tracts are SVI tracts, and only 28% of Texas census tracts experiencing load shed are SVI tracts.



(d) Census tracts with relatively larger (although still minority) indigenous populations. Note that these areas coincide with load shedding and both high-risk, vulnerable regions 1 and 2.

Figure 2: Load shed (in the absence of undergrounding decisions and equity considerations), visualized with red bubbles on the map, occurs almost exclusively in the vulnerable areas highlighted in Figure 1. However, each of the social vulnerability indices fail to consistently capture these areas as vulnerable; in all three cases, the percent of census tracts experiencing load shed which are categorized as “vulnerable” is either approximately as high (both Justice40 metrics, Figures 2a, 2b), or substantially lower (SVI, Figure 2c) than the overall percentage of vulnerable tracts across the entire state of Texas. Figure 2d shows that census tracts with larger (although still minority) indigenous tracts exist in both vulnerable regions 1 and 2, and appear to be disproportionately subject to load shed.

A lot of effort has gone into the design of vulnerability indices as Justice40 and SVI. However, the challenge in defining such an index is the necessary aggregation of the statistics of a population in various census tracts. To explain this better, we first focus on Texas and explain its socioeconomic geography and physical network characteristics that create overlapping vulnerabilities. This overlap makes it difficult to reduce load shed from PSPS events. Figure 1 shows how the less population dense areas of northern (Region 1) and western (Region 2) Texas have higher concentrations of lines with higher wildfire ignition risk (Figure 1a), higher percentages of low-income households (Figure 1c), and higher percentage minority census tracts (Figure 1d); however, the cost to underground lines in central and west Texas is also higher—in many cases surpassing $100 million per line (Figure 1b). Furthermore, even when the budget *is* high enough to underground those lines, relatively few individuals receive benefit due to the more rural location. The overlap between the location of vulnerable communities and the cost to underground the power lines serving them lends some intuition about why rural, low-income, minority, or high-wildfire-risk groups in Texas may not be prioritized when allocating investments for power line undergrounding. This is particularly harmful because, without power line undergrounding, these vulnerable tracts are disproportionately subject to load shed. When relying only on power shutoffs (and not undergrounding) to control wildfire ignition risk, Figure 2 shows that load is shed predominantly in high-risk Regions 1 and 2.

Despite the fact that Regions 1 and 2 are subject to high wildfire-ignition risk, high likelihood of power outages in a PSPS event, and an anticipated lower likelihood of receiving undergrounding investment, we also see in Figure 2 that the Justice40 and the CDC's SVI metrics do not identify these tracts experiencing power outages as being any more vulnerable than the census tracts not experiencing power outages. A natural question is whether this is due to 1) the fact that the Justice40 indices are nationally sorn, whereas the socioeconomic and climate vulnerability within Texas might reflect different trends or 2) the fact that Justice40 defines general climate vulnerability as opposed to wildfire vulnerability, specifically. To test this, we modified the Justice40 criteria to only consider Texas percentiles of wildfire spread risk, as opposed to national percentiles of many types of climate risks (e.g. flood risk, agriculture loss rate, wildlife loss, etc). Interestingly, even this "modified Justice40" index fails to capture the vulnerability of the census tracts in the highlighted Regions 1 and 2 (Figure 2). Indeed, there are cumulative network effects that all three metrics (Justice40, SVI, and modified Justice40) do not capture. In particular, we focus often in this work on the impact on indigenous communities, since baseline models (i.e., models not including any Policy constraints to protect vulnerable groups) for where to optimally de-energize and underground lines result in maximum load shed on this population (Table 2a **baseline** model, for more details, see Appendix D). We highlight in Figure 2d areas which bear most of the load shed in the network, and it is clear that the vulnerability indices can only capture a part of the affected areas. In fact, indigenous populations are estimated (through our simulations) to experience nearly twice as much load shed as the average Texas resident, yet are no more likely to live in a Justice40, modified Justice40, or SVI tract than any other Texas resident[6]. We hypothesize that this is because indigenous populations make up such a small fraction of the total population of each census tract that their relative disadvantage[7] is overlooked when other groups within the census tract are not disadvantaged.

The correlation plot shown in Figure 3 makes these observations more concrete. Figure 3 shows that while the characterization of a census tract as "vulnerable" by either the Justice40, modified Justice40, or SVI metrics does correlate with socioeconomic notions of vulnerability (shown in blue), in particular, the percent of the census tract that lacks health insurance or is below the poverty line, these metrics fail to identify wildfire ignition risk as a vulnerability metric, as well as identify minority indigenous communities within census tracts who experience poverty at nearly twice the rate of white households in Texas as per the

[6]Our simulations in Table 5 of Appendix D.3 show that the indigenous groups experience approximately 2.52% of load demanded that is shed whereas the overall population experiences 1.22% of load demanded that is shed when there is no undergrounding budget or equity objectives.

[7]An estimated 22.5% of indigenous American groups were below 125% of the poverty line compared to 13.3% of white and 24% of Hispanic groups, which are the other two groups prone to at- or above-average load shed in this case. However, white and Hispanic groups made up 48% and 40% of the Texas population respectively, and indigenous groups make up less than 1% of the Texas population. This makes aggregation a likely explanation for the discrepancy in budget allocation and lack of characterization of indigenous groups as belonging to Justice40 census tracts [25, 26, 27]

GIDTR	percentile below poverty line	percentile indigenous	percentile ignition risk
110093	65	94	88
120013	53	85	94
120013	57	94	94
220006	52	99	99
220020	52	99	99
220077	77	99	99

Table 1: **A subset of census tracts categorized as "not vulnerable" for each of the three indices (Justice40, Justice40 modified for Texas and wildfire risk, alone, and the CDC's SVI metric). See Table S1 in Appendix C.7 for the full list of such census tracts.**

US Census Bureau's 2022 ACS estimates [27, 25, 26]. When specifically investigating Texas census tracts with high wildfire ignition risk as defined in the United States Geological Survey (USGS) Wind-enhanced Fire Potential Index (WFPI), lower income, and a disproportionate fraction of Texas's indigenous population, we can verify that this combination is often missed by all three indices: Justice40, modified Justice40, and the CDC's SVI. Table 1 shows a subset of census tracts that the Justice40, modified Justice40, and SVI criteria fail to designate as vulnerable, despite being above the 50th percentile for low income, and at very high percentiles for ignition risk (over 88%) and the fraction of the census tract that is indigenous (over 85%). For the full list of these census tracts, see Appendix C.7.

To analyze the effects of an equitable resource allocation according to the Justice40 framework, we solve a MIP with the objective of minimizing the total network load shed subject to power flow constraints, budget constraints, limits on acceptable levels of wildfire ignition risk (per line, and across the whole network), and POLICY constraints. From this framework, we want to understand three main factors:

1. Who is subject to power outages?
2. What proportion of the investment is allocated to different groups?
3. Who gets most of the *benefit* from the investment?

In other words, *do the* POLICY *constraints result in the intended effect?*

Policy Constraints Alone Yield Little to No Improvement We find that when we do incorporate POLICY constraints either by proportionally allocating 40% of the *budget* or by proportionally allocating 40% of the *load shed reduction* to vulnerable (e.g., Justice40, modified Justice40 or SVI) tracts, indigenous populations see no per capita reductions in load shed compared to the baseline case (when no POLICY constraints are used). In fact, Figure 4b shows how every racial group—including indigenous groups—experiences *more* load shed after either Justice40 POLICY constraint is implemented, even though the budget allocation *does* becomes increasingly allocated to indigenous groups. It is likely that the discrepancy in the allocation of budget and the corresponding benefits (in terms of alleviating power outages) stems from POLICY constraints channeling funds towards census tracts with lower population density or tracts where the cost to underground power lines is higher. Consequently, although the per capita investment for indigenous groups may be more substantial, the per capita reduction in load shed remains unimproved. We discuss the data in more detail in the next section.

Potential Solution using Group-Level Protections. From the above-mentioned results, it is clear that protecting indigenous populations from load shed is challenging due to their minority status in each census tract and their residence in areas where undergrounding

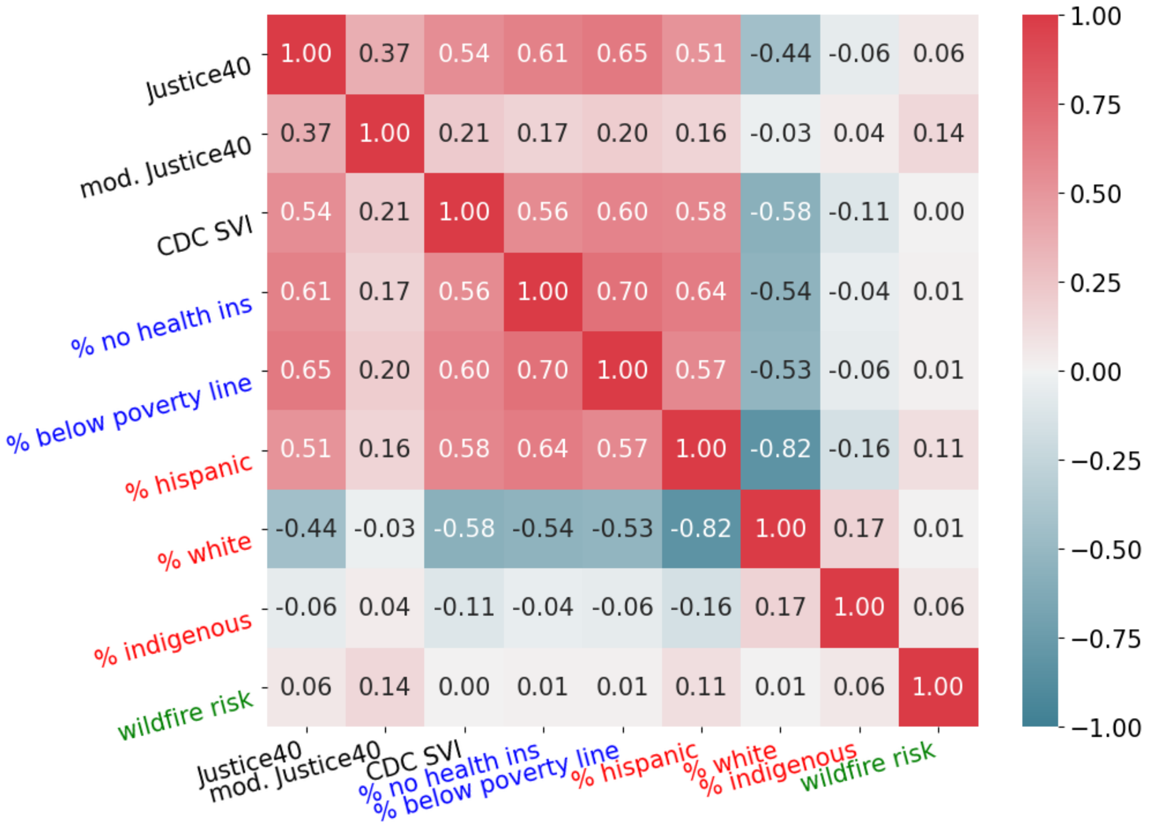


Figure 3: Vulnerability metrics (in black text labels) are positively correlated with each other, as well as by lack of health insurance, impoverished status (blue text labels), and percentage of the tract that is hispanic. Percentage white is negatively correlated with each of these, and percentage indigenous and wildfire risk maintain close to no correlation. The fact that wildfire ignition risk is not correlated with these vulnerability metrics shows a failure of these metrics to quantify this type of climate risk. The fact that indigenous groups do not correlate with measures of vulnerability imply a data aggregation issue, as US Census Data shows higher poverty rates among indigenous communities [25, 26, 27].

is expensive and wildfire ignition risk is high.[8] This motivates the advantage of employing *group-level protections* to ensure that each population group of interest (e.g., racial groups) is able to receive the appropriate level of resources. We can employ group-level protections by implementing a percentage-based Min-Max Fairness (MMF) framework in the optimization model when making undergrounding and de-energization decisions. That is, instead of using our standard objective to minimize total load shed in the network, we can instead minimize the maximum percentage of a group's load that is shed, which we refer to as the Equity objective. By using this percentage-based MMF framework, we account for the total load demanded by each group, allowing the program to mitigate the effects of minority status on the likelihood that a group receives relief from load shed. We summarize the results of using any combination of Equity objective and Policy constraint for a $1 billion budget in Table 2. Table 2 shows the percent of each group's load demanded that is shed and an "unfairness" ratio, which is the ratio of the group's percent load shed to the overall population's percent load shed.

Our baseline model (M1) in Table 2a seeks to minimize the total load shed in the network (i.e., there is no Equity objective) subject to power flow and budget constraints only (i.e., there are no Policy constraints). Under this baseline for a $1 billion budget, indigenous

[8]Note that low income communities may be more likely to reside in high wildfire risk areas given lower housing prices in wildfire-prone areas [28].

(a) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under only POLICY constraints when there is a $1 billion budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Unfairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
Baseline - M1	None	None	0.33 (1.0)	**0.37 (1.12)**	0.33 (1.0)	**0.48 (1.45)**	0.29 (0.88)	0.07 (0.21)	**0.97 (2.94)**	0.08 (0.24)
M2	Justice40	Proportional Budget Expenditure	0.35 (1.0)	**0.41 (1.17)**	0.34 (0.97)	**0.48 (1.37)**	0.34 (0.97)	0.06 (0.17)	**1.07 (3.06)**	0.07 (0.2)
M3	Justice40	Proportional Load Shed Reduction	0.45 (1.0)	0.46 (1.02)	0.4 (0.89)	**0.58 (1.29)**	0.47 (1.04)	0.07 (0.16)	**1.41 (3.13)**	0.12 (0.27)
M4	Justice40 (Modified)	Proportional Budget Expenditure	0.35 (1.0)	**0.41 (1.17)**	0.34 (0.97)	**0.49 (1.4)**	0.34 (0.97)	0.06 (0.17)	**1.09 (3.11)**	0.07 (0.2)
M5	Justice40 (Modified)	Proportional Load Shed Reduction	0.8 (1.0)	0.88 (1.1)	0.77 (0.96)	**0.96 (1.2)**	0.8 (1.0)	0.49 (0.61)	**1.29 (1.61)**	0.26 (0.33)
M6	SVI	Proportional Budget Expenditure	0.37 (1.0)	**0.42 (1.14)**	0.34 (0.92)	**0.51 (1.38)**	0.35 (0.95)	0.07 (0.19)	**1.18 (3.19)**	0.08 (0.22)
M7	SVI	Proportional Load Shed Reduction	0.37 (1.0)	**0.43 (1.16)**	0.37 (1.0)	**0.49 (1.32)**	0.37 (1.0)	0.05 (0.14)	**0.88 (2.38)**	0.07 (0.19)

(b) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under the EQUITY objective and POLICY constraints when there is a $1 billion budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Unfairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low Income	Hispanic	White	Black	Indigenous	Asian
Equity - M8	None	None	0.55 (1.0)	0.55 (1.0)	0.46 (0.84)	**0.67 (1.22)**	**0.61 (1.11)**	0.08 (0.15)	**0.75 (1.36)**	0.16 (0.29)
Equity - M9	Justice40	Proportional Budget Expenditure	0.51 (1.0)	0.55 (1.08)	0.45 (0.88)	0.67 (1.31)	0.52 (1.02)	0.07 (0.14)	**0.75 (1.47)**	0.11 (0.22)
Equity - M10	Justice40	Proportional Load Shed Reduction	0.72 (1.0)	0.63 (0.88)	0.62 (0.86)	0.71 (0.99)	0.71 (0.99)	0.7 (0.97)	0.79 (1.1)	0.71 (0.99)
Equity - M11	Justice40 (Modified)	Proportional Budget Expenditure	0.56 (1.0)	0.59 (1.05)	0.5 (0.89)	**0.69 (1.23)**	0.6 (1.07)	0.14 (0.25)	**0.77 (1.38)**	0.12 (0.21)
Equity - M12	Justice40 (Modified)	Proportional Load Shed Reduction	1.19 (1.0)	1.0 (0.84)	1.02 (0.86)	1.14 (0.96)	1.14 (0.96)	1.14 (0.96)	1.27 (1.07)	1.14 (0.96)
Equity - M13	SVI	Proportional Budget Expenditure	0.56 (1.0)	0.61 (1.09)	0.51 (0.91)	**0.7 (1.25)**	0.59 (1.05)	0.18 (0.32)	**0.79 (1.41)**	0.13 (0.23)
Equity - M14	SVI	Proportional Load Shed Reduction	0.57 (1.0)	0.56 (0.98)	0.46 (0.81)	**0.67 (1.18)**	**0.66 (1.16)**	0.09 (0.16)	**0.75 (1.32)**	0.11 (0.19)

Table 2: **Percentage load shed across different groups, for all combinations of EQUITY objective (group-level protections) and POLICY constraints with a $1 billion budget. The red cells indicate that the % load shed is above a threshold of 1%, and the red, bolded text indicates groups experiencing over 1.1 times the percent load shed of the overall population. Note that for all models not employing the EQUITY objective,indigenous populations experience both disproportionately high load shed, as well as relatively unfair load shed. Similarly, hispanic and uninsured groups also experience relatively unfair percentages of load shed. Incorporating the EQUITY objective reduces much of this unfairness, and, with the exception of M12, leads to acceptable load shed for each remaining group. From these two criteria, M10 has the best performance. We note that these results were run up to at most a 5 percent optimality gap in the MIP.**

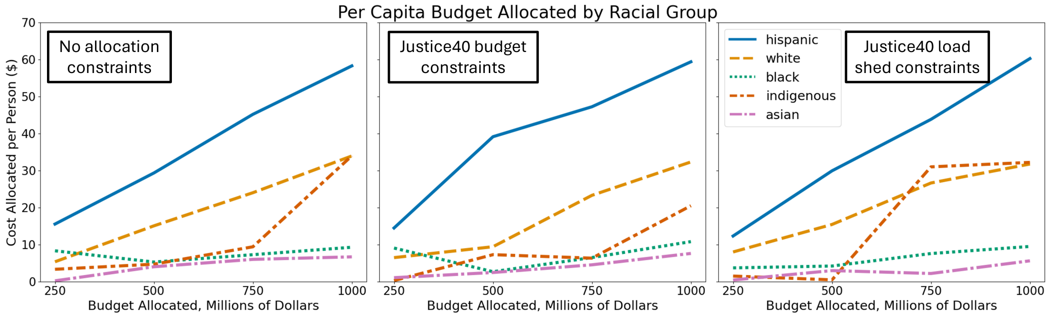
populations experience 0.97% of load shed, which is almost three times higher than that of the overall population. Next, we test various optimization models that try to minimize the total load shed in the network, while ensuring that 40% of the benefit goes to vulnerable tracts (using POLICY constraints), in models M2 to M7. For each of these, with the exception of M7, Table 2a shows a consistently higher percent of load shed for indigenous populations, thus, not having a considerable impact on protecting these vulnerable communities. Even for model M7, the indigenous load shed reduction is minimal, with an improvement of only 0.04% over the baseline. We also observe that, in general, no group is substantially "better off" (in terms of percent of load shed) after implementing POLICY constraints—in fact, they are usually *worse* off—and the modified Justice40 index type performs markedly more poorly than the other indices, despite being more specific to Texas and focusing on wildfire hazards.

Next, we add group-level protections using EQUITY objectives to minimize the maximum percentage of load shed across various groups. This model still has budget and power flow constraints, and we also consider models with both an EQUITY objective and POLICY constraints. The results for these models M8-M14 are reported in Table 2b. Indeed, we can see that, with the exception of M12, using EQUITY objectives with and without POLICY constraints, reduces the percentage of load shed across *all* populations to be within 0.80%. While all other groups experience some increase in percent load shed, these increases are fairly reasonable; for example, in model M10, the percent of load shed experienced by Asian households increases from 0.08% (baseline) to 0.71%, which is a large jump nominally, but still meets the sub-1% threshold for what we consider to be an acceptable percentage of load shed. Furthermore, this 0.71% figure is very similar to other load shed percentages experienced by other groups in model M10. With the exception of black and Asian households who experience disproportionately low load shed in any case, the load shed across the other groups is fairly balanced, with differences between groups being less than 0.3% for M8-11, M13-14. This is reflected also in the reduced unfairness scores in Table 2b. While indigenous and Hispanic groups still face more than 1.1 times the overall load shed in many cases, these unfairness ratios are significantly lower than those shown in Table 2a. For M10, we see that we achieve both relative fairness *and* acceptable levels of load shed for all groups considered.

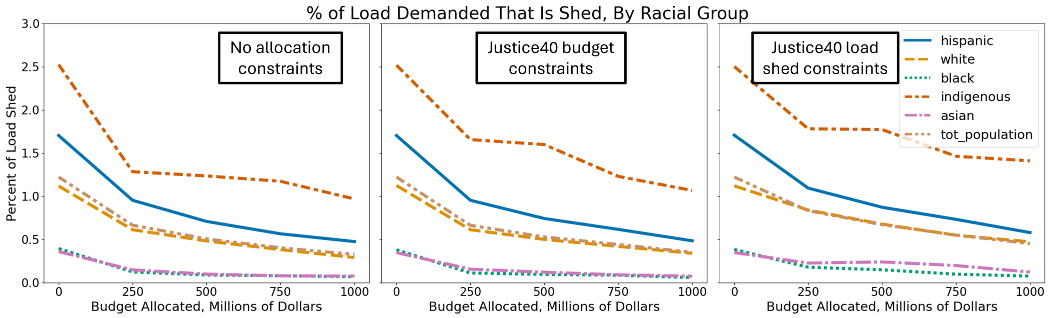
Overall, we show a significant benefit of using EQUITY objectives along with POLICY constraints derived from Justice40 vulnerability indices, where the latter alone are unable to provide low load shedding protections to indigenous populations. While Table 2 only shows the results for the $1 billion budget, we note that the MMF framework which promotes the most load shed relief for indigenous groups under the $1 billion budget also promote load shed relief compared to the baseline at the $500 million and $750 million budgets (see the the figures in Appendix D.2). Hence, we find that in order to see meaningful reductions in indigenous load shed and keep the load shed of other groups below a reasonable threshold, our study finds two requirements: 1) a sufficiently high budget, in our case, at least $500 million, and 2) a MMF framework that minimizes the maximum percentage of a group's load demanded that is shed. This latter requirement is necessary to place indigenous groups on equal priority with different racial, ethnic, and other groups which make up a higher percentage of Texas' total population.

Discussion

In this paper, we consider how to make power line undergrounding and de-energization decisions in wildfire-prone regions as a multi-criteria decision with the following considerations: (i) we want to have minimal (or close to minimal) total load shed in the network, (ii) we would like the total wildfire ignition risk in the network to remain within set limits, and (iii) we would like to allocate benefits fairly across various groups. While considerations (i) and (ii) are relatively straightforward, developing a "fair" allocation policy (iii) is significantly



(a) Normalized cost allocated to group in the baseline case (no equity constraints) (left), the case when constraining 40% of the budget to go to Justice40 communities (center), and the case when constraining 40% of load shed reduction to go to Justice40 communities (right).



(b) Percent of load demanded that is shed by racial group in the baseline case (no equity constraints) (left), the case when constraining 40% of the budget to go to Justice40 communities (center), and the case when constraining 40% of load shed reduction to go to Justice40 communities (right).

Figure 4: **The top row in this figure** shows normalized cost allocated to each racial group. We see that there is negligible investment differences in between the baseline case (top left) and the case where we constrain 40% of the budget to go to Justice40 (top center). At $1 billion allocated, the Justice40 budget constraint provides *less* budget than the baseline to indigenous groups. If we constrain 40% of load shed improvement to go to Justice40 groups (top right), indigenous groups see their investment per capita more than doubling over the baseline once a $750 million investment is reached. However, this budget allocation increase does not translate to load shed reduction. **The bottom row of the figure** shows load shed trends by racial group remain relatively consistent across each of these constrained cases. In fact, at $750 million investment, indigenous load shed is *higher* when adding the Justice40 constraint for load shed improvement than the baseline case, at 0.136 kWh shed per indigenous person versus 0.110 kWh shed per indigenous person.

more challenging. Ideally, we would like to preferentially protect populations that are both more likely to experience emergency power shutoffs and less likely to effectively cope with the negative impacts of power outages.

First, we analyzed Justice40 notions of fairness through Policy constraints in a MIP model of a high-fidelity, synthetic transmission network in Texas [22] with the objective of minimizing total network load shed. Specifically, we considered constraints that proportionally allocate 40% of the total budget to vulnerable communities or proportionally allocate 40% of the total load shed reduction to vulnerable communities as defined by three vulnerability indices: the Justice40 index, the SVI, and a modified Justice40 index that only accounts for Texas percentiles of wildfire risk. The optimal solution to these programs generally led to increased load shed outcomes for *all* racial and socioeconomic groups. In particular, these Policy constraints often fail to protect indigenous populations who experience nearly double the poverty rate and double the anticipated load shed as the average Texan. We believe the reasons for the misalignment between the *intent* of the Justice40 initiative with each of the vulnerability indices and the *realized benefit* (or lack thereof) to indigenous and high-risk communities after implementing Policy constraints is due to (i) information loss due to data aggregation, and (ii) lack of context-specific vulnerability criteria. Indeed, the challenge of using any vulnerability index (including existing indices like the Justice40 and SVI metrics) lies in the fact that the creating the index requires some degree of data aggregation, which leads to homogenization of the population of a census tract and conceals vulnerable minority populations. Further, since climate impact is so diverse in the factors that result in compounded vulnerability of populations, we believe that factors such as ignition risk, forest cover, humidity (i.e., wildfire risk predictors) coupled with socioeconomic vulnerability indicators would be more appropriate to consider for mitigating wildfire risk, although we note that the "curse of aggregation" would still apply. Indeed, we showed that when modifying the Justice40 initiative criteria to only consider Texas wildfire spread risk (as opposed to national percentiles of a plethora of different, often unrelated climate risks), we had similarly poor load shed outcomes for indigenous groups.

The inability of these aggregated vulnerability indices to identify and appropriately allocate resources to vulnerable minority populations motivates the use of explicit *group protections.* Percentage-based equity objectives like the percentage-based MMF objective are group-size conscious, which prevents minority subpopulations within census tracts from being overlooked during the optimization routine in a way that vulnerability indices cannot. Furthermore, such an objective, by construction, balances "fair" load shed outcomes with total load shed in the network. While group-size-conscious allocation mechanisms may not be advantageous in certain contexts, the inability of the Justice40 and SVI metrics to identify indigenous disadvantage makes this particular context of budget allocation for power line undergrounding a feasible candidate for a group-size-conscious allocation policy. We note that our results about higher indigenous load shed under emergency power shutoff policies may not be strictly generalizable to other wildfire-prone regions with different network geometries and demographic distributions (e.g., California), but our general warning about the possibility of overlooking vulnerable minority groups within census tracts is still applicable.

In conclusion, we showed that percentage-based, MMF-fair objectives are able to protect the interest of vulnerable minority groups within census tracts once a sufficient budget, in this case, at least $500 million, is allocated. This contrasts with the load shed results when using policy constraints alone. Since data aggregation is necessary to form a vulnerability index, disadvantaged populations can not be protected by vulnerability indices if they form a small or negligible proportion of a census tract. Furthermore, when using policy constraints alone, lack of context-specificity in defining who is vulnerable prevents a generalized policy from being helpful in a specific setting.

Methods

We use a Mixed Integer Program (MIP) to simulate operation of a synthetic Texas transmission network. Pre-processing steps allocate population to each node on the network and wildfire ignition risk to each line of the network. Using a Bθ DC power flow approximation, daily operational decisions are made to dictate generation, necessary load shed, and line de-energization choices to meet an acceptable risk threshold. In addition, a single set of undergrounding investment decisions are made across the simulated time periods. For these results, we simulate a representative high-risk five-day period in July 2021. From these simulations, budget allocation and load shed can be attributable to different groups. Complete mathematical models are defined in Appendix B.

Acknowledgments

The authors would like to acknowledge the Partnership for an Advanced Computing Environment (PACE) at the Georgia Institute of Technology [29] for the hardware used to complete simulations. In addition, the following software was used for simulations: Gurobi [30], Julia [31], JuMP [32], and PowerModels [33]. R.P and D.M. acknowledge support from NSF AI Institute for Advances in Optimization (AI4OPT), #2112533. S.G. and M.P. acknowledge support from NSF CAREER Award #2239824.

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A Case Study

In this section, we discuss the elements of our case study. First, we discuss the synthetic network used in our study, previewing some of the characteristics of the network that make optimization for equity meaningful. Then, we discuss the data used to inform our models, including how we define risk in the case study.

A.1 Synthetic Network

In this study, we use the synthetic Texas7k transmission network test case, developed by the Texas A&M PERFORM group. This test case provides a realistic approximation of the area covered by the Electric Reliability Council of Texas (ERCOT) [34, 22]. Synthetic grids like Texas7k are useful because they mimic the characteristics of actual grids [22] while not disclosing sensitive data about the properties of these grids, including locations of power lines and generators and the amount of load. For these reasons, synthetic networks have are frequently used in related research [35, 16, 36].

While Texas does not currently use organized PSPS events, Texas has experienced more than 4,000 power line-caused wildfires from 2011-2014 [37], as well as unplanned rolling blackouts from extreme weather [38], making PSPS events a possible future solution. More recently, the Smokehouse Creek fire was potentially ignited by power infrastructure sparking the largest wildfire in the state of Texas [39]. Furthermore, the increase in power outages due to ice storms and other extreme weather in Texas has led to increased popularity of line undergrounding as a method of preventing these rolling blackouts [40].

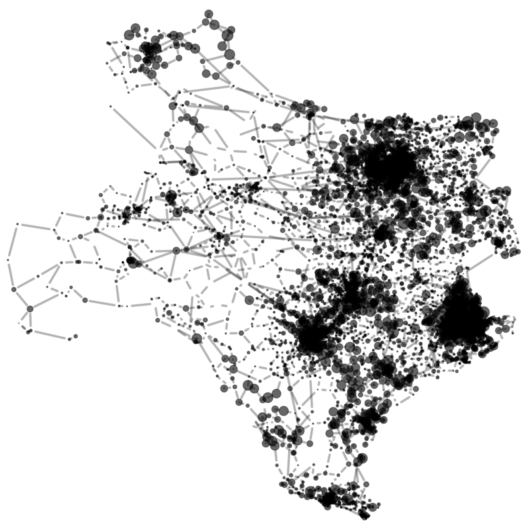


Figure 5: Population served by each bus in the Texas7k transmission network where each dot represents a bus and each line is a transmission line. The size of the dot corresponds to the amount of population served at that bus.

A.1.1 Hourly Loads

We consider time indices representing one-hour periods and select $T = 120$ to model 5 days during a high wildfire risk time of year to give a representative operational time span. However, the Texas7k test case [34, 22] provides a single snapshot of nominal load demands. The multi-period optimization problem considered in this paper requires extending these test cases with time-varying load profiles. For this purpose, we modify the nominal loads according to the hourly, daily, and weekly scaling factors derived in [41] to create hourly load curves for each day during the representative time span.

A.1.2 Demographic Data

To make generalizations about the impact of switching and line undergrounding on the overall Texas population, the synthetic transmission network needs to be augmented with demographic data. We use the census tract definitions that were in effect from 2010-2020. The demographic group variables of interest include the census tracts and their associated total populations, number of individuals in each demographic group (e.g., race, below-poverty line, insurance status, etc.). The vulnerability groups of interest are defined by the Justice40 initiative and the CDC's SVI. While the Justice40 initiative gives us the vulnerable tracts directly, we select vulnerable tracts from the CDC's SVI metric by considering tracts that are at or above the 75th percentile of at least one of four different categories of burden. For more background on each of these metrics, as well as the datasets and data types used in this study, see Appendix C. We attribute the demographic data from each census tract to each load-supplying bus in the Texas7k network using the procedure outlined in Appendix C.C.6.

B Grid and Switching Model

We first introduce the framework used to model line switching from PSPS events on an electric power transmission network. Then, we discuss modifications to this model to incorporate line undergrounding and the addition of equity considerations. This section will be fairly general and high-level, as to be applicable to other case studies. Appendix C discusses the data sources and assumptions specific to our case study.

B.1 Network Description

Following standard modeling approaches in power engineering, we consider an electric transmission network comprised of buses (nodes) connected by power lines (edges). Each line has a rated limit indicating the capacity for power to traverse that line along with other parameters to model the physical characteristics. Each bus can have an associated set of generators that produce power and an amount of load that consumes power. As is commonly the case in transmission planning contexts, the system is modeled using the DC power flow approximation which is described further in Appendix BB.3.

B.2 Parameter and Variable Definitions

For a given network, let $\mathcal{N}$ be the set of buses, $\mathcal{L}$ be the set of transmission lines, and $\mathcal{G}$ be the set of generators. Let $\mathcal{T} = \{1, \dots, T\}$ be the considered set of time indices over the period of a day, where T is the final time period. Let $\mathcal{D} = \{1, \dots, D\}$ be the considered set of days, where D is the final day. We define a 100 MVA per unit (p.u.) base power. The following network parameters are provided for all lines $\ell \in \mathcal{L}$:

- b^ℓ, line susceptance in p.u.,
- $\overline{f}^\ell$, the power flow limit in p.u.,
- r_d^ℓ, the wildfire risk incurred if line ℓ is energized on day d as a unitless non-negative number,

- $n^{\ell,\text{to}}$ and $n^{\ell,\text{fr}}$, *to* and *from* buses, respectively, where positive power flows from the *from* bus to the *to* bus,
- $\overline{\delta}^{\ell}$ and $\underline{\delta}^{\ell}$, upper and lower voltage angle difference limits in radians, respectively,
- l^{ℓ}, line length in miles.

$\mathcal{L}$ is further divided in to $\mathcal{L}_d^{high}$, $\mathcal{L}_d^{med}$, and $\mathcal{L}_d^{low}$ to indicate the set of lines that have high, medium, or low wildfire risk on day d, respectively. These categories are further described in Appendix B.C.5. For all generators $i \in \mathcal{G}$, define the parameters:

- $\overline{p}_g^i$ and $\underline{p}_g^i$, upper and lower power generation limits, respectively, in p.u.,
- n^i, bus at which generator i is located.

For all buses $n \in \mathcal{N}$, define the parameters:

- $p_{l,d,t}^n$, power demand (load) at bus n at time period $t \in \mathcal{T}$ on day $d \in \mathcal{D}$ in p.u.,
- $\mathcal{G}^n$, the set of generators located at bus n,
- $\mathcal{L}^{n,\text{to}}$ and $\mathcal{L}^{n,\text{fr}}$, the subset of lines $\ell \in \mathcal{L}$ with bus n as the designated *to* bus and bus n as the designated *from* bus, respectively.

The operation of the network during a multi-time-period PSPS event is characterized by the following set of variables using the BΘ representation of the DC power flow model:

- $p_{g,d,t}^i$, power generated at unit $i \in \mathcal{G}$ at time period $t \in \mathcal{T}$ on day $d \in \mathcal{D}$ in p.u.,
- $\theta_{d,t}^n$, voltage angle at bus $n \in \mathcal{N}$ at time period $t \in \mathcal{T}$ on day $d \in \mathcal{D}$ in radians,
- $p_{ls,d,t}^n$, load shedding at bus $n \in \mathcal{N}$ at time period $t \in \mathcal{T}$ on day $d \in \mathcal{D}$ in p.u.,
- $f_{d,t}^{\ell}$, power flowing from bus $n^{\ell,\text{fr}}$ to bus $n^{\ell,\text{to}}$ along line $\ell \in \mathcal{L}$ at time period $t \in \mathcal{T}$ on day $d \in \mathcal{D}$ in p.u.,
- $z_d^{\ell} \in \{0,1\}$, state of energization of line $\ell \in \mathcal{L}_d^{\text{high}}$ and $\ell \in \mathcal{L}_d^{\text{med}}$ on day $d \in \mathcal{D}$. If $z_d^{\ell} = 0$, then line ℓ is de-energized, and if $z_d^{\ell} = 1$, then line ℓ is energized. Note that the line's energization state is constant for all $t \in \mathcal{T}$ on day $d \in \mathcal{D}$. For all $\ell \in \mathcal{L}_d^{\text{low}}$, $z_d^{\ell} = 1$. Let $\mathcal{L}_d^{\text{switch}} = \mathcal{L}_d^{\text{high}} \cup \mathcal{L}_d^{\text{med}}$

B.3 Operational and Physical Constraints

We define the following constraints for the DC Operational Transmission Switching Problem (DC-OTS),

$$\underline{p}_g^i \leqslant p_{g,d,t}^i \leqslant \overline{p}_g^i, \qquad \forall i \in \mathcal{G},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1a}$$

$$0 \leqslant p_{ls,d,t}^n \leqslant p_{l,d,t}^n, \qquad \forall n \in \mathcal{N},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1b}$$

$$-\overline{f}^{\ell} z_d^{\ell} \leqslant f_{d,t}^{\ell} \leqslant \overline{f}^{\ell} z_d^{\ell}, \qquad \forall \ell \in \mathcal{L}_d^{\text{switch}},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1c}$$

$$-\overline{f}^{\ell} \leqslant f_{d,t}^{\ell} \leqslant \overline{f}^{\ell}, \qquad \forall \ell \in \mathcal{L} \setminus \mathcal{L}_d^{\text{switch}},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1d}$$

$$\underline{\delta}^{\ell} z_d^{\ell} + \underline{M}(1 - z_d^{\ell}) \leqslant \theta_{d,t}^{n^{\ell,\text{fr}}} - \theta_{d,t}^{n^{\ell,\text{to}}} \leqslant \overline{\delta}^{\ell} z_d^{\ell} + \overline{M}(1 - z_d^{\ell}) \qquad \forall \ell \in \mathcal{L}_d^{\text{switch}},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1e}$$

$$\underline{\delta}^{\ell} \leqslant \theta_{d,t}^{n^{\ell,\text{fr}}} - \theta_{d,t}^{n^{\ell,\text{to}}} \leqslant \overline{\delta}^{\ell}, \qquad \forall \ell \in \mathcal{L} \setminus \mathcal{L}_d^{\text{switch}}, \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1f}$$

$$-b^{\ell}(\theta_{d,t}^{n^{\ell,\text{fr}}} - \theta_{d,t}^{n^{\ell,\text{to}}}) + |b^{\ell}|\underline{M}(1 - z_d^{\ell}) \leqslant f_{d,t}^{\ell} \leqslant -b^{\ell}(\theta_{d,t}^{n^{\ell,\text{fr}}} - \theta_{d,t}^{n^{\ell,\text{to}}}) + |b^{\ell}|\overline{M}(1 - z_d^{\ell}), \quad \forall \ell \in \mathcal{L}_d^{\text{switch}},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1g}$$

$$-b^\ell(\theta_{d,t}^{n^{\ell,\mathrm{fr}}} - \theta_{d,t}^{n^{\ell,\mathrm{to}}}) \leqslant f_t^\ell \leqslant -b^\ell(\theta_{d,t}^{n^{\ell,\mathrm{fr}}} - \theta_{d,t}^{n^{\ell,\mathrm{to}}}), \qquad \forall \ell \in \mathcal{L} \setminus \mathcal{L}_d^{\mathrm{switch}},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}, \tag{1h}$$

$$\sum_{\ell \in \mathcal{L}^{n,\mathrm{fr}}} f_{d,t}^\ell - \sum_{\ell \in \mathcal{L}^{n,\mathrm{to}}} f_{d,t}^\ell = \sum_{i \in \mathcal{G}^n} p_{g,d,t}^i - p_{l,d,t}^n + p_{ls,d,t}^n, \qquad \forall n \in \mathcal{N},\ \forall d \in \mathcal{D},\ \forall t \in \mathcal{T}. \tag{1i}$$

where (1a) enforces lower and upper generation limits, (1b) constrains any load shedding to be nonnegative and less than the load demanded at that time at that bus, (1c) and (1d) enforce line flow limits, (1e) and (1f) constrain angle differences across lines, (1g) and (1h) model the DC power flow approximation, and (1i) ensures power balance at all buses in the network. In equations (1e) and (1g), $\overline{M}$ and $\underline{M}$ are big-M constants and are set to 2π and -2π respectively for the numerical experiments in this paper. Note that when a line is energized (i.e., $z^\ell = 1$), (1e) simplifies to (1f) and (1g) simplifies to (1h).

We then constrain the total risk from all energized above-ground lines to be below a given threshold, R_{PSPS}, on each day:

$$\sum_{\ell \in \mathcal{L}} z_d^\ell r_d^\ell \leq R_{PSPS} \qquad \forall d \in \mathcal{D}. \tag{2}$$

B.4 Line Undergrounding Formulation

In this paper, we discuss line undergrounding as a method of line hardening. This work could be replicated or extended with other types of line hardening, including structural upgrades to power infrastructure, line insulation, and cutting back vegetation surrounding power lines. Let the subset $\mathcal{L}^{\mathrm{harden}} \subseteq \mathcal{L}$ be the set of lines that are candidates for hardening/maintenance where $\mathcal{L}^{\mathrm{harden}} = \mathcal{L}_d^{\mathrm{high}} \bigcup_{d \in \mathcal{D}} \mathcal{L}_d^{\mathrm{med}}$. We assume users have access to the following parameters:

i) $\beta \in [0, 1]$, the proportional reduction in wildfire risk due to line hardening or maintenance measures. Note: for undergrounding considered in this paper, we choose $\beta = 1$, i.e., undergrounding a line entirely eliminates the line's ignition risk,
ii) ϕ_{ug}^ℓ, the cost of undergrounding line ℓ in millions of dollars per line.

For all $\ell \in \mathcal{L}^{\mathrm{harden}}$, we introduce the variable $y^\ell \in \{0, 1\}$, which indicates whether a line has been undergrounded ($y^\ell = 1$) or not ($y^\ell = 0$). Note for $\ell \in \mathcal{L} \setminus \mathcal{L}^{\mathrm{harden}}$, we set $y^\ell = 0$.

We assume that the entire length of line ℓ is undergrounded. Hardening partial segments of lines may provide better outcomes by targeting investments in specific areas; however, this does not change the fundamental characteristics of the problem. Extensions can be made to consider partial undergrounding such as in [42], though this paper does not include a power flow model.

There is no benefit to simultaneously hardening and de-energizing a line since de-energizing a line reduces its risk to zero while hardening a line reduces the risk by β at a cost of ϕ_{ug}^ℓ per mile. Thus, we impose the following constraint to prevent simultaneous de-energizing and hardening a line:

$$z_d^\ell = y^\ell, \qquad \forall \ell \in \mathcal{L}_d^{\mathrm{high}},\ \forall d \in \mathcal{D}. \tag{3}$$

$$(1 - z_d^\ell) + y^\ell \leqslant 1, \qquad \forall \ell \in \mathcal{L}_d^{\mathrm{med}},\ \forall d \in \mathcal{D}. \tag{4}$$

We note that (3) ensures lines in the highest-risk category are either off (de-energized) or undergrounded, removing the risk by one method or the other. Alternatively, (4) allows for the lines in the medium-risk category to optionally be de-energized, undergrounded, or left above ground and energized. Regardless, in both categories, undergrounded lines will remain energized.

We introduce a budget, B (in millions of dollars) to limit the resources available for line undergrounding. We use a conservative fixed cost of \$7 million per mile for undergrounding [43]. The total cost of undergrounding is precomputed as ϕ_{ug}^{ℓ}, defined above. This introduces the following constraint:

$$\sum_{\ell \in \mathcal{L}^{\text{harden}}} \phi_{\text{ug}}^{\ell} y^{\ell} \leqslant B. \tag{5}$$

With the inclusion of undergrounding, we can reformulate equation (2) to

$$\sum_{\ell \in \mathcal{L}} r_d^{\ell}(z_d^{\ell} - y^{\ell}) \leqslant R_{PSPS}, \qquad \forall d \in \mathcal{D}. \tag{6}$$

B.5 Equity Considerations

A set of demographic features is assigned to each bus based on the demographic features of nearby census tracts (see Appendix C.6 for the procedure). There are two main feature types that we consider for this study: "demographic" characteristics and "vulnerability" characteristics. Demographic characteristics (such as income bracket or racial group), are characteristics which partition the population, and, while possibly correlated with vulnerability, do not imply vulnerability directly. Vulnerability characteristics, on the other hand, is a binary indicator variable which assigns a 1 to census tracts that meet a given definition of vulnerability, and otherwise assigns a 0. We consider two ways of promoting group fairness, given these two types of features:

1. We can minimize disparate impacts of load shedding across different *demographic* groups by altering the objective. In particular, we can do this by implementing group protections by minimizing the maximum percent of a group's load demanded that is shed. In the study, we call these EQUITY objectives. In general, the literature often refers to such objectives as MMF objectives.
2. We can preferentially allocate resources to groups with *vulnerability* characteristics by imposing proportionate policy-level constraints to enforce that either i) a certain percentage of the budget must be allocated to vulnerable populations, or ii) certain amount of mitigated load shed is attributable to vulnerable populations. To stay in line with the Justice40 initiative, we choose this proportion to be 40% of the budget or load shed reduction, respectively. In the study, we call these POLICY constraints.

The following subsections show how to modify the base model to account for the incorporation of equity into the model.

B.5.1 Fairness Parameters

To introduce equitable considerations in to our problem, we introduce the following demographic parameters for any demographic group $m \in M$:

- $\text{abs}_{n,m}$ represents the absolute population at bus n of demographic m,
- $\text{pct}_{n,m}$ represent the percentage of the population at bus n that belongs to demographic m,
- vm_n, the percentage of population at bus n that belongs to vulnerable populations based on a given metric

We then have the aggregate parameters $ls_{\text{tot},0}$ and $ls_{\text{vm},0}$ which represent the total load shed seen with a budget of 0 for a given objective and the total load shed associated with vulnerable populations with a budget of 0 for a given objective, respectively.

From here, we can define the percentage of load demanded by each demographic group that is shed. Note, we assume that load at a bus is allocated proportionally by the populations present at the bus. First we define the total load shed attributable to each group, $\mathrm{P}_{ls,m}$, and the total load demanded by each group, $\mathrm{P}_{d,m}$:

$$\mathrm{P}_{ls,m} = \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} \mathrm{pct}_{n,m} p^n_{ls,t,d},$$

$$\mathrm{P}_{d,m} = \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} \mathrm{pct}_{n,m} p^n_{d,t,d}.$$

B.5.2 POLICY Constraints

We introduce two constraints that serve to prioritize vulnerable populations. One emphasizes the allocation of budget to vulnerable communities. The other ensures load shed reduction is seen by vulnerable populations as budget is increased.

Budget Constraint We introduce a constraint that ensures 40% of the budget spent on line undergrounding is associated with the vulnerable populations. To do this, we model the cost of underground line ℓ, ϕ^ℓ_{ug}, as being split equally between the two buses at each end of the line, $n^{\ell,\mathrm{to}}$ and $n^{\ell,\mathrm{fr}}$. We then define the budget spent on vulnerable populations as:

$$vm_{\mathrm{bud}} = \sum_{\ell\in\mathcal{L}} y^\ell \frac{\phi^\ell_{\mathrm{ug}}}{2}\left(vm_{n^{\ell,\mathrm{to}}} + vm_{n^{\ell,\mathrm{fr}}}\right).$$

To ensure budget is allocated according to the vulnerable populations, we enforce:

$$vm_{\mathrm{bud}} \geq 0.4 * B. \tag{7}$$

Load Shed Reduction Constraint We introduce a constraint that ensures 40% of the reduction in load shed compared to the zero-budget case within the same objective is seen by vulnerable populations. We then define the load shed seen by vulnerable populations as:

$$ls_{\mathrm{vm}} = \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} p^n_{ls,d,t} vm_n.$$

Next we calculate the total load shed in the network given this combination of constraint and budget:

$$ls_{\mathrm{tot}} = \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} p^n_{ls,d,t}.$$

Then to ensure load shed reduction is seen by vulnerable populations:

$$\frac{ls_{\mathrm{vm},0} - ls_{\mathrm{vm}}}{ls_{\mathrm{tot},0} - ls_{\mathrm{tot}}} \geq 0.4. \tag{8}$$

B.6 Objectives

We now introduce three different types of objectives. First, a baseline objective that seeks to minimize the total load shed in the network. Then, an objective to minimize the maximum percent of load demanded that is shed.

B.6.1 Baseline

Our baseline objective is to minimize total load shed in the network. Let P be the total demand in the network over all time periods and S represent the proportional load shedding in the network over the given time periods:

$$P = \sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} p^n_{d,t,d},$$

$$S = \frac{1}{P}\left(\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}} p^n_{ls,t,d}\right). \tag{9}$$

The objective function becomes

$$\min_{p_g,\theta,f,p_{ls},z,y} \quad (9) \ \text{ s.t. } (1),\ (3)-(6). \tag{10}$$

With the inclusion of the POLICY constraints described in Section B.5.2, the objective becomes (11) or when considering budget (12):

$$\min_{p_g,\theta,f,p_{ls},z,y} \quad (9) \ \text{ s.t. } (1),\ (3)-(6),\ (7) \tag{11}$$

$$\min_{p_g,\theta,f,p_{ls},z,y} \quad (9) \ \text{ s.t. } (1),\ (3)-(6),\ (8). \tag{12}$$

B.6.2 EQUITY Objectives

We attempt to minimize the maximize disparity seen across a set of demographics groups, M. We implement an EQUITY objective that considers the percentage of load demanded that is shed. A percentage-based MMF framework is preferable in this context because minority groups are given more weight in the MIP objective than a nominal MMF framework. The nominal framework would be more likely to overlook small minority groups with relatively little load shed compared to the total load shed on the network.

Under this EQUITY objective, we define the auxiliary variable, aux_{pct}, to minimize the maximum proportional load demanded that is shed across each group:

$$\frac{\mathrm{P}_{ls,m}}{\mathrm{P}_{d,m}} \leq \text{aux}_{\text{pct}} \qquad \forall m \in M. \tag{13}$$

We define the following MIP to minimize the maximum percent load shed across groups:

$$\min_{p_g,\theta,f,p_{ls},z,y} \quad \text{aux}_{\text{pct}} \ \text{ s.t. } (1),\ (3)-(6),\ (13). \tag{14}$$

With the inclusion of the POLICY constraint considering budget, the objective becomes (15) or when considering load shed reduction, (16):

$$\min_{p_g,\theta,f,p_{ls},z,y} \quad \text{aux}_{\text{pct}} \ \text{ s.t. } (1),\ (3)-(6),\ (7),\ (13) \tag{15}$$

$$\min_{p_g,\theta,f,p_{ls},z,y} \quad \text{aux}_{\text{pct}} \ \text{ s.t. } (1),\ (3)-(6),\ (8),\ (13). \tag{16}$$

See Table 3 for a list of all models considered in this study.

C Data

In this appendix, we discuss the data sources used for this study.

Model	Objective	Policy Constraint	
		Vulnerability Index	Constraint Type
Baseline - M1	min total load shed ((9))	N/A	N/A
M2	min total load shed ((9))	Justice40	Prop. Budget Expenditure, i.e., $vm_{\text{bud}} \geq 0.4B$ (7)
M3	min total load shed ((9))	Justice40	Proportional Load Shed Reduction i.e., $\frac{ls_{\text{vm},0} - ls_{\text{vm}}}{ls_{\text{tot},0} - ls_{\text{tot}}}$ (8)
M4	min total load shed ((9))	Justice40 (Mod.)	Prop. Budget Expenditure, i.e., $vm_{\text{bud}} \geq 0.4B$ (7)
M5	mine total load shed ((9))	Justice40 (Mod.)	Proportional Load Shed Reduction i.e., $\frac{ls_{\text{vm},0} - ls_{\text{vm}}}{ls_{\text{tot},0} - ls_{\text{tot}}}$ (8)
M6	min total load shed ((9))	SVI	Prop. Budget Expenditure, i.e., $vm_{\text{bud}} \geq 0.4B$ (7)
M7	minimize the total load shed ((9))	SVI	Proportional Load Shed Reduction i.e., $\frac{ls_{\text{vm},0} - ls_{\text{vm}}}{ls_{\text{tot},0} - ls_{\text{tot}}}$ (8)
Equity-M8	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	N/A	N/A
Equity-M9	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	Justice40	Prop. Budget Expenditure, i.e., $vm_{\text{bud}} \geq 0.4B$ (7)
Equity-M10	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	Justice40	Proportional Load Shed Reduction i.e., $\frac{ls_{\text{vm},0} - ls_{\text{vm}}}{ls_{\text{tot},0} - ls_{\text{tot}}}$ (8)
Equity-M11	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	Justice40 (Mod.)	Prop. Budget Expenditure, i.e., $vm_{\text{bud}} \geq 0.4B$ (7)
Equity-M12	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	Justice40 (Mod.)	Proportional Load Shed Reduction i.e., $\frac{ls_{\text{vm},0} - ls_{\text{vm}}}{ls_{\text{tot},0} - ls_{\text{tot}}}$ (8)
Equity-M13	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	SVI	Prop. Budget Expenditure, i.e., $vm_{\text{bud}} \geq 0.4B$ (7)
Equity-M14	$\min \max_{\text{racial group } g}$ percentage load shed for group g ((13))	SVI	Proportional Load Shed Reduction i.e., $\frac{ls_{\text{vm},0} - ls_{\text{vm}}}{ls_{\text{tot},0} - ls_{\text{tot}}}$ (8)

Table 3: **Summary of all models considered in this work.**

C.1 US Census Data

We obtained demographic data for each of the Texas census tracts whose power is supplied by ERCOT from US Census Data. While Texas was most recently re-districted in 2021 [44], certain important data fields were not available on these new districts, so we utilized the old districting maps that were in place from 2010 to 2020. To obtain data by census tract for total population, median income, and number of individuals in each racial group, we used the 2019 Planning Database, version 2 [45]. To get the latitude and logitude of the center of population for each census tract, we used center of population data from the 2010 Decennial census [46], which was the most recently available center of population data for this districting.

C.2 The Justice40 Initiative

The Justice40 initiative was established in Executive Order 14008 in January 2021 by the Biden-Harris administration. The Justice40 initiative maintains that 40% of the "benefits" of government investment in transportation, power, environmental, and other systems should flow to "disadvantaged communities" [13], which, at a US Census Tract level, have already been defined on the basis of income, energy access, housing access, and environmental burden. In general, according to the US Council on Environmental Quality [47], to qualify for the Justice40-designation, a census tract must either

a) "meet the thresholds for at least one of the tool's categories of burden," or

b) be "within the boundaries of a federally recognized tribe."

The former generally requires that a census tract be above the 65th percentile nationwide for the percentage of the population which is considered low-income (below 200% of the federal poverty line) AND at the 90th percentile nationwide for one of the many different types of climate burden. Different types of climate burden include wildfire risk, flood risk, agriculture loss rate, population loss rate, and others [47]. Since the Justice40 metric considers national percentiles and Texas has higher climate risk and poverty levels than much of the United States, we see that nearly 50% of census tracts served by ERCOT are categorized as Justice40 tracts. Furthermore, this metric involves climate risks that are not limited to wildfire risk, including flood risk, agriculture loss rate, and others. Because of this, in this study, we also compute a modified Justice40 metric, which categorizes a tract as vulnerable if that tract is above the 50th percentile of Texas census tracts for the percentage of the tract which is low-income, and above the 75th percentile of Texas census tracts for the wildfire risk subcategory of the Justice40 dataset. With this definition, only around 11% of census tracts are considered vulnerable. It is also worth noting that the way that the Justice40 initiative designates wildfire risk in each census tract is different from the USGS WFPI data [23] that we use to assign wildfire risk to power lines. The WFPI data computes risk of *wildfire ignition* from present conditions, described further in Appendix C.C.4. The Justice40 calculation comes from 30-year projections of *wildfire spread* models to compute the projected wildfire risk to properties over that 30-year horizon [47, 48]. Since we are modeling daily operational de-energization decisions, and investing in infrastructure to support these PSPS events, we model acute ignition risk instead of long-term, long-duration spread models.

The other criterion that results in immediate selection as a Justice40 census tract is whether a census tract is "within the boundaries of a federally recognized tribe." This criterion is meant to capture the disproportionately high rate of poverty experienced by indigenous Americans [49]; however, this criterion only accounts for tribes with a designated land area. Importantly, this criterion *does not* account for indigenous populations that live outside of these designated areas or indigenous populations that do not have such a designated area. Hence, the Justice40 initiative may not truly capture indigenous poverty from groups not living on reservations.

C.3 The CDC/ATSDR Social Vulnerability Index

The Center for Disease Control and Prevention (CDC) and Agency for Toxic Substances and Disease Registry (ATSDR) have a joint metric of social vulnerability given in terms of an SVI [15]. The goal of this SVI is to designate communities which may have additional difficulty coping with a disaster event. This SVI considers four main "themes" of risk: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type/transportation. In this study, we classify a census tract as vulnerable if that census tract is is at or above the 75th percentile of burden out of all the census tracts in Texas for at least one of these four themes. We use the 2010 SVI dataset to remain consistent with the 2010 census tracts [15].

C.4 USGS Wildland Fire Potential Index

The USGS WFPI is a data set compromised of unitless risk values ranging from 0 to 247 for each 1km by 1km "pixel" of the United States. These values are updated daily along with a 7-day forecast of expected risk values. The USGS bases this data on the following [23]:

- Maximum Live Ratio,
- Dead Fuel Moisture,
- Fuel Model,
- Wind Reduction Factor,
- Normalized Difference Vegetation Index,
- Relative Greenness,
- 10-hour Dead Fuel Moisture,
- Wind Speed,
- Rain,
- Dry Bulb Temperature.

The USGS WFPI provides a proxy for the risk of ignition from electric infrastructure since higher WFPI values have, historically, correlated to larger fires and fires that have spread to burn more area [23].

C.5 Wildfire Risk Values

The wildfire ignition risk posed by an energized power line depends on a number of factors involving the environmental conditions around the line and the line's physical characteristics. Translating these factors into numeric risk values is challenging (see, e.g., [50]) and requires detailed data that are not available for our test cases. In place of more targeted data, we use the USGS WFPI as mentioned in Section C.C.4.

Historically, wildfire season in the western United States typically spans from late summer to early fall; however, recent wildfire seasons have been lengthening [51]. Therefore, our analyses use data from June 1 to October 31, which we will refer to as the wildfire season.

We assign a unitless wildfire risk value r_d^ℓ for each line $\ell \in \mathcal{L}$ for each day $d \in \mathcal{D}$ in the considered network in the wildfire season over three years (2019, 2020, and 2021). To find this value, we find the average pixel risk, $\bar{r}_p$ by taking the mean of all pixel values on all lines from the data used. We find the standard deviation on this data as well, σ_p. We then define a high-risk pixel to be an pixel with a value more than one standard deviation above the mean:

$$r_{p,l,d}^h = \left\{ \begin{array}{ll} r_{p,l,d}, & \text{if } r_{p,l,d} \geq \bar{r_p} + \sigma_p \\ 0, & \text{if } r_{p,l,d} < \bar{r}_p + \sigma_p \end{array} \right\}. \tag{17}$$

We calculate the risk value r_d^ℓ by integrating the high-risk pixel values along each line. This method balances the risk contributions from both long line lengths and underlying risk of the terrain. "Line length" is a characteristic that has been correlated with higher ignition risk [50] but this processing avoids a situation where a long line with relatively low risks along the entire length appears much riskier than a shorter line with points of much higher ignition risks.

For each day simulated, we first determine if the wildfire threat is high enough to necessitate de-energizing lines via a threshold on the total risk during that day. Let R_d be the total wildfire risk the network poses if all lines $\ell \in \mathcal{L}$ are energized on day d, i.e.:

$$R_d = \sum_{\ell \in \mathcal{L}} r_d^\ell.$$

In our assessment methodology, operators are required to reduce the total risk of the network by making line de-energization decisions during any day for which $R_d \geqslant R_{\text{PSPS}}$, where R_{PSPS} is a specified system-wide de-energization threshold. Conversely, if $R_d < R_{\text{PSPS}}$, then the risk the network poses is not great enough to require the widespread de-energization of lines. For the purposes of this paper, R_{PSPS} is set to 6×10^8. Results and figures will indicate what overall threshold was applied to the network.

Two more thresholds are used for the network to split $\mathcal{L}_d$ in to $\mathcal{L}_d^{high}$, $\mathcal{L}_d^{med}$, and $\mathcal{L}_d^{low}$. These thresholds, R_{high} and R_{low}, are used to indicate the highest acceptable risk before lines must be de-energized or undergrounded and the lowest risk below which lines are not considered for undergrounding or de-energization:

$$\forall \ell \in \mathcal{L}, \left\{ \begin{array}{lr} \ell \in \mathcal{L}_d^{high}, & \text{if } r_d^l \geq R_{\text{high}} \\ \ell \in \mathcal{L}_d^{med}, & \text{if } R_{\text{low}} \leq r_d^l < R_{\text{high}} \\ \ell \in \mathcal{L}_d^{low}, & \text{if } r_d^l < R_{\text{low}} \end{array} \right\}. \tag{18}$$

For the results in this paper, R_{high} and R_{low} are set to 1×10^6 and 1, respectively. Note, this means all lines with nonzero risk are allowed to be de-energized or undergrounded. These values were chosen to allow enough lines to be candidates for undergrounding such that the MIP produces non-trivial solutions.

C.6 Mapping Demographic Features to Buses

A challenge arises in associating each census tract to one or more load-supplying buses in the synthetic network, or, equivalently, assigning all or some fraction of the population at a census tract to each load-supplying bus in the network. Matching the population data to the transmission bus would require models of the distribution systems, which are not available. We therefore make the modeling decision to match census tracts to buses based on the distance between the bus and the population center of the census tract, that is, we assume the closer a bus is to a census tract's center of population, the more likely the census tract has its power supplied, at least in part, by that bus. Hence, the goal is to find a reasonable edge cover of the bipartite graph consisting of the set of load-supplying buses and the set of census tracts. We use the following algorithm to assign tracts to buses.

Let $\mathcal{C}$ denote the set of census tracts and $\mathcal{N}$ represent the set of buses. Let d_{cn} represent the distance between the center of population of census tract c and bus n. Each census tract $c \in \mathcal{C}$ has a feature vector f_c. Our goal is to map these census tract features onto the set of load-supplying buses in the transmission network to obtain a feature vector on each of the buses, f_n for all $n \in \mathcal{N}$. Also helpful to us is the construction of an $|\mathcal{C}| \times |\mathcal{N}|$ matrix A where entry a_{ij} tells us the fraction of census tract $i \in \mathcal{C}$ which is assigned to bus $j \in \mathcal{N}$. We take a three-pass approach.

1. For every census tract $c \in \mathcal{C}$, we initialize the radius r_c as the minimum distance from c to any other bus in the transmission network. If a bus n is within the radius r_c for any $c \in \mathcal{C}$, we say that the bus has been *assigned*.
2. For any bus n that has not yet been assigned, we find the closest census tract c to n. Let this closest distance be given by r_n. We then update $r_c \leftarrow \max\{r_c, r_n\}$. Now, bus n has been assigned.
3. For every tract $c \in \mathcal{C}$, we consider the subset of buses $\mathcal{N}^c_{r_c}$ within a distance r_c from c. We divide the population of c between each bus $n \in \mathcal{N}^c_{r_c}$ proportionally based on their relative distance from c. That is, the fraction of f_c that is assigned to bus $n' \in \mathcal{N}^c_{r_c}$ is

$$a_{cn'} = \frac{d_{cn'}}{\sum_{i \in \mathcal{N}^c_{r_c}} d_{ci}}. \tag{19}$$

At the termination of this algorithm, we have a sparse matrix, A, where the columns represent the load-supplying buses, the rows represent each applicable census tract in Texas, and each entry a_{ij} is the "fraction" of each census tract i that is assigned to each bus j. Finally, we have that the demographic feature vector for bus $n \in \mathcal{N}$ is given by $f_n = \sum_{c \in \mathcal{C}} f_c \cdot a_{cn}$

Mapping wildfire ignition risk to census tracts When we consider the wildfire ignition risk at each census tract, we use the following rough heuristic. For every line, we compute the line risk using the high risk integral method described in Appendix CC.5. We then ascribe half of the wildfire risk to each terminating bus of the line. Each census tract is served by at least one bus, so the ignition risk at every census tract is the sum of the risks of each of the buses serving load to that census tract where we use the procedure outlined in Appendix CC.6 to estimate which buses serve which census tracts.

C.7 "Missed" Vulnerable Tracts

Table 4 gives the set of Texas census tracts which are above the 75th percentile for the fraction of the population that is indigenous, above the 75th percentile for wildfire ignition risk (derived from WFPI data described in Appendix C.C.5), and above the 50th percentile for number of people below the poverty line, but that were *not* characterized as vulnerable by the Justice40, modified Justice40, and SVI criteria. We also show the percentile without

Table 4: **List of disadvantaged census tracts that every vulnerability index categorized as not vulnerable.**

GIDTR	percentile uninsured	percentile impoverished	percentile indigenous	percentile ignition risk
110093	69.8	64.8	94.5	88.3
110965	73.9	51.0	76.9	75.1
120013	32.9	52.7	84.9	95.7
120063	32.9	52.7	84.9	84.3
120112	52.8	76.2	94.4	89.6
120171	55.7	66.5	90.4	83.9
140066	9.2	80.1	75.1	82.5
210028	20.3	58.4	97.5	89.6
210029	50.0	56.8	94.2	94.4
210030	69.4	62.2	93.2	91.7
210053	50.5	62.4	96.2	78.3
210075	30.7	61.2	77.5	80.4
210207	25.7	59.4	89.6	84.2
210293	59.8	61.0	94.5	88.7
220006	78.5	52.4	100.0	99.3
220020	78.5	52.4	100.0	99.7
220026	54.6	56.5	95.7	95.7
220057	29.9	57.9	98.0	97.2
220077	25.5	76.7	99.4	99.3
220109	38.0	52.9	92.0	95.4
240084	44.4	64.3	75.3	94.7
240121	67.0	64.5	86.4	93.7
240148	67.0	64.5	86.4	91.8
240160	54.1	62.8	86.9	84.8
240162	12.3	74.4	98.1	93.2
240193	18.7	51.6	91.2	84.7

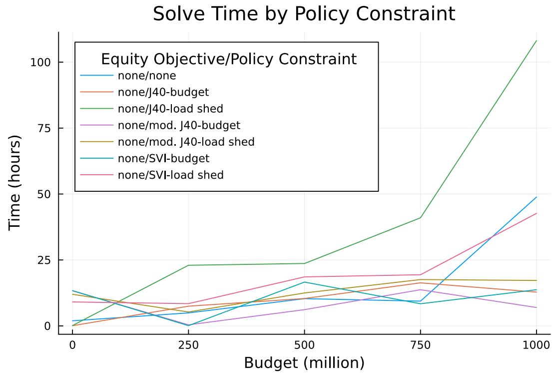
health insurance for reference. One might note from Table 4 that the impoverished percentile is not often *too* high; indeed, the maximum percentile impoverished in the table is 80.1 for GIDTR 140066, and most values are between the 50th and 60th percentiles. Given that indigenous poverty rates are nearly double that of the overall population [25, 26, 27], this indicates that indigenous populations are almost always the minority of the census tract that they live in, and the majority population of those tracts is not disadvantaged. Hence, these lower poverty percentiles do not indicate that these indigenous populations are not statistically poorer (we know that they are from the data), but rather, they indicate that these groups tend to live in areas where the majority population is less disadvantaged on average than the indigenous population.

D Optimization Results

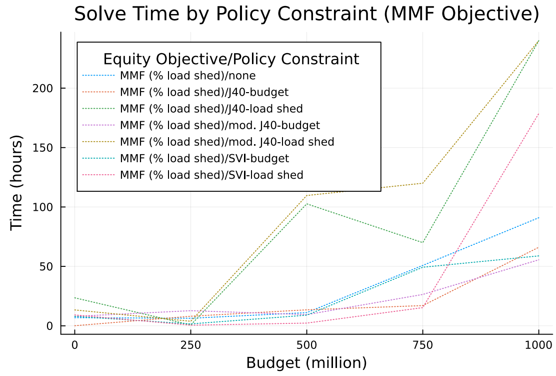
D.1 Optimization Software, Set Up, and Solve Time

Optimization problems were solved using Gurobi 10.0.0 [30]. To implement the optimization formulations, we used Julia 1.8.0 [31] with JuMP 1.18.1 [32] along with the data input functionality of PowerModels.jl 0.21.0 [33]. Simulations were completed on the Partnership for an Advanced Computing Environment (PACE) at the Georgia Institute of Technology [29] using the framework and parameters described by Appendix B and C, respectively. For nonzero budgets, we warm-started the simulation with the results from the same model on the previous budget. All simulations are run to for 5 days of a MIP gap of 1%. Any simulations that are outside the 1% MIP gap are run for an additional 5 days with a warm-start of the last found incumbent. Both of these 5-day computation times are done with MIP focus set to 2. Any simulations that are still outside the 1% MIP gap are run for an additional 10 days, again warm-started from the last found incumbent, or until they reach a 1% MIP gap. This 10 day computation time is done with MIP focus set to 3 to prioritize improvement in the best bound. After 20 days of computation time per scenario, MIP gaps are reported, with all scenarios finishing within a 5% MIP gap. Solution times are shown in Figures 6a and 6b.

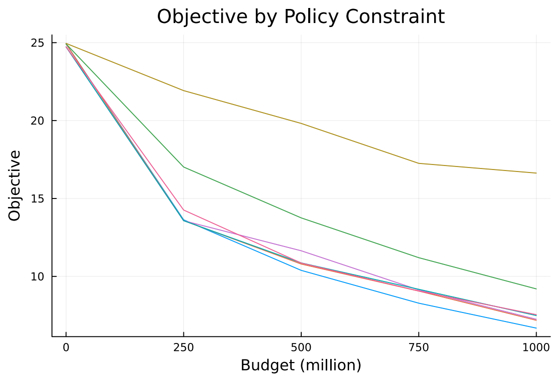
While not all simulations converge to a 1% MIP gap, we note the monotonically decreasing objective across budgets, see Figures 6c and 6d. Note the objective value for the baseline objective displays total network load shed while the EQUITY objective values portray the maximum percentage of demanded load that is shed for a given group, resulting in different scales. All simulations with a baseline objective solve to within a 1% MIP gap. Two combinations of the EQUITY objective with the both the modified and original Justice 40 load shed constraints converge to within a 5% MIP gap. All other cases with the EQUITY objective converge to within a 1% MIP gap.



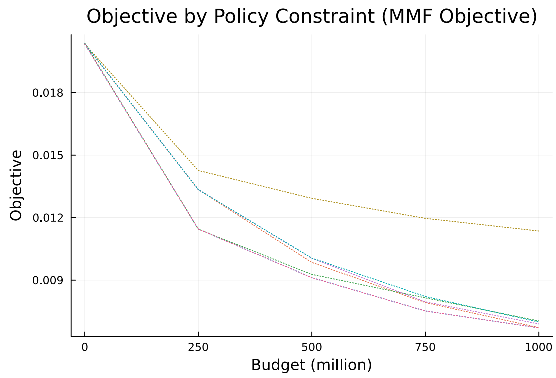
(a) Solution times by budget for simulations with the baseline objective (minimize total loadshed) and various POLICY constraints.



(b) Solution times in hours by budget for simulations with the EQUITY objective and various POLICY constraints.



(c) Objective values by budget for simulations with the baseline objective (minimize total loadshed) and various POLICY constraints.

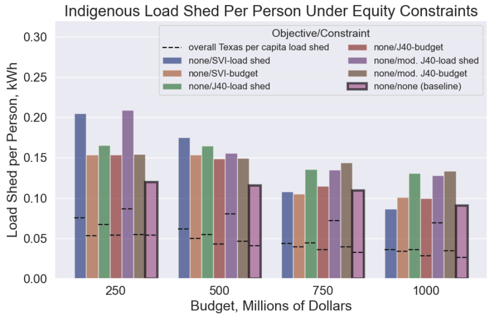


(d) Objective values by budget for simulations with the EQUITY (minimize the maximumum percent of load shed by group) objective and POLICY constraints.

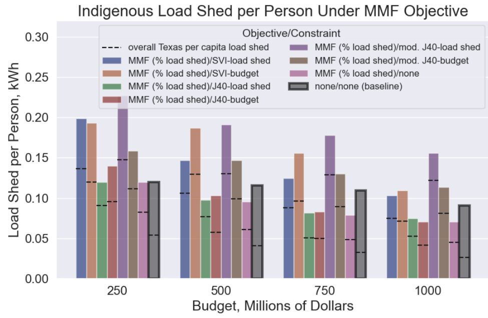
Figure 6: Solve times, MIP gaps, and Objective values for listed POLICY constraints with both the baseline objective and the EQUITY objective.

D.2 Indigenous Load Shed

Figure 7 shows comparisons of each combination of EQUITY objective and POLICY constraint in terms of the quantity of load shed per indigenous person under each resource allocation framework. In the figure, there are two important observations. First, the overall Texas per capita load shed, shown by the horizontal dotted line on each bar of the barplot, increases when the EQUITY objective is used instead of the baseline objective. This is not unexpected given that we are trading off between the efficiency of the resource allocation, and the equity of the resource allocation. In Appendix D.D.3, one can see the magnitude of this trade-off in terms of the percent of each group's load demanded that is shed, and we argue that these increases in total load shed are not unreasonable.



(a) Comparison of normalized indigenous load shed across cases with the objective of minimizing total network load shed with different equity constraints.



(b) Comparison of normalized indigenous load shed across cases with a MMF objective where we balance the percent of total load shed by racial group.

Figure 7: Normalized indigenous load shed across multiple budgets when only equity constraints are used (left) and when the percentage-based MMF objective is used with and without equity constraints (right). The "budget" and "load shed" modifiers are there to say whether the program allocates 40% of the budget or 40% load shed reduction to the vulnerable groups identified by the preceding vulnerability metric. The horizontal dashed lines on each bar show the normalized overall load shed in the network for that case. When only considering equity objectives, we see that none of these constraints decisively reduce load shed for indigenous groups. When we add the percentage-based MMF objective by group, we find that once a $500 million budget is achieved, the objective to minimize the maximum percent of load shed by each racial group coupled with either no equity constraints or Justice40 constraints consistently leads to lower indigenous load shed than the baseline. We also see that indigenous per capita load shed is always much higher than the overall per capita load shed under the baseline objective, whereas the indigenous per capita load shed is closer to even with the overall per capita load shed with the MMF objective. However, this comes at the cost of increases in overall per capita load shed.

The second observation deals with how effective the Equity objective is at reducing indigenous load shed relative to the baseline (no Equity objective, no Policy constraints, shown by the bolded bar on the plot). In Figure 7a, we see Policy constraints alone do not improve indigenous load shed outcomes until a $750 million budget is met, and even in the $750 million and $1 billion budget cases, the improvement is marginal. In comparison, in Figure 7b we see reductions in indigenous load shed with the Equity objective when as little as $250 million is allocated. With the exception of the case where we use the modified Justice40 Policy constraint by reduction in percent load shed with the Equity objective, *all* other Equity models decrease the per capita load shed experienced by indigenous populations compared to the baseline once a $500 million budget is allocated. At the $1 billion budget, we see a reduction of roughly 1MWh of load shed affecting indigenous communities between the baseline and those under the equity objectives (excluding the case using the modified Justice40 policy constraint). This is equivalent to nearly 35 more homes being able to maintain power for an entire day[9].

D.3 Load Shed Results

In this section, we discuss the full load shed results for each budget we considered, from 0 budget allocated to $1 billion allocated, in $250 million increments for each combination of Policy constraint and Equity Objective. In Appendix D D.3.1, we show tables for the total load shed in megawatt hours per group and in AppendixD.3 D.3.2, we show tables of the percent of load demanded that is shed by group as well as the "relative unfairness" in load shed , which is defined as the ratio of the percent of load shed experienced by the particular group to the percent of load shed experienced by the overall population served by

[9]This is based on an assumed 29kWh of daily power consumption.

the ERCOT network. All results shown in this table are from runs of the MIP described in Appendix B up to a 5% MIP gap with most of the results converging with under a 1% gap.

D.3.1 Total Load Shed By Group

As was discussed at length in this article, one of situations in which vulnerability indices can fall short is when there are very small minority populations that become homogenized with a larger minority group within census tracts. In Table 5, we see the nominal load shed results in megawatt hours for eight groups considered in this studied, one of which is the overall population, five of which are racial groups, and two of which are measures of economic vulnerability, when there is no budget allocated (Table 5), and when there is $1 billion allocated. Without any undergrounding, we see that the baseline load shed on the network is about 2500 MWh, and when we substitute the EQUITY objective, the total load shed increases by around 1000 MWh, depending on the specific policy being used. Because there is no budget for undergrounding, this 1000 MWh increase is simply from choosing to switch off more lines than is necessary to reduce risk below a reasonable threshold, which would likely never be done in practice. However, this does highlight the trade-off between equity and efficiency when trying to implement fairness into optimization models in practice. In Table 6, we can see how power line undergrounding can dramatically reduce the load shed on the network; in the baseline case, the overall load shed drops by about 73% after allocating a $1 billion budget. We see small increases in total network load shed between about 50 and 150 MWh, excluding Model M5, which is an outlier when incorporating POLICY constraints alone, but see larger increases in total network shed compared to the baseline when incorporating the EQUITY objective, where we see increases between about 375 and 820 MWh (excluding outlier M12). The discrepancy in load shed outcomes between the baseline and EQUITY objective cases is due to a possible combination of increased load shed on mid-risk census tracts and less-efficient power line undergrounding (i.e., power lines serving fewer people are undergrounded, but these lines serve high-vulnerability populations).

In nominal terms, we see that Hispanic and white groups experience a large percentage of the total load shed experienced by the overall population; however, this result is reflective of these groups' relative share of the population, not some inherent higher likelihood of experiencing a power outage, which is apparent when considering each group's percent of load that is shed, (discussed in Appendix D.3.2). Thus, the nominal load shed can be deceiving; most notably, indigenous groups make up an small quantity of the nominal load shed in the network—reflecting that they make up a tiny fraction of the overall Texas population—but have a disproportionately high percentage of their load demanded that is shed.

D.3.2 Percent of Load Demanded That is Shed and Relative Unfairness in Load Shed

It is nearly impossible to ascertain how equitable the switching and power line undergrounding decisions are without some degree of normalization for different group sizes. In this subsection, we discuss the percent of load demanded that is shed by each group and give a "relative unfairness" metric. This metric computes the ratio of the percent of load shed experienced by the group to the percent of load shed experienced by the overall population. We designate an "unfair" outcome as one in which a group experiences more than 1.1 times the overall percent load shed for a budget of $1 billion or more or more than 1.3 times if the budget is under $1 billion, and we bold and color the text in those cells red to call attention to these unfair outcomes. Tables 7, 8, 9, and 10 show the percentage of load demanded and relative unfairness in outcome by group for the $0, $250 million, $500 million, and $750 million cases, respectively.

(a) **Nominal load shed in megawatt hours by group under only POLICY constraints when there is no budget allocated for power line undergrounding.**

	Policy Constraint		Nominal Load Shed (MWh)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
M1 - BL	None	None	2491	456	276	1304	1029	89	13	28
M2	Justice40	Proportional Budget Expenditure	2491	458	275	1304	1034	86	13	27
M3	Justice40	Proportional Load Shed Reduction	2491	458	276	1307	1031	87	13	27
M4	Justice40 (Modified)	Proportional Budget Expenditure	2473	458	275	1305	1014	88	14	27
M5	Justice40 (Modified)	Proportional Load Shed Reduction	2494	459	276	1310	1030	89	14	27
M6	SVI	Proportional Budget Expenditure	2473	458	275	1305	1014	88	14	27
M7	SVI	Proportional Load Shed Reduction	2473	459	273	1299	1019	87	13	28

(b) **Nominal load shed in megawatt hours by group under under the EQUITY objective and POLICY constraints when there is no budget allocated for power line undergrounding.**

	Policy Constraint		Nominal Load Shed (MWh)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
Equity-M8	None	None	3523	602	401	1571	1569	237	12	85
Equity-M9	Justice40	Proportional Budget Expenditure	3777	619	419	1576	1847	203	12	85
Equity-M10	Justice40	Proportional Load Shed Reduction	3320	577	379	1579	1508	135	12	47
Equity-M11	Justice40 (Modified)	Proportional Budget Expenditure	3581	595	403	1562	1703	176	12	79
Equity-M12	Justice40 (Modified)	Proportional Load Shed Reduction	3915	601	426	1576	1881	240	12	145
Equity-M13	SVI	Proportional Budget Expenditure	3581	595	403	1562	1703	176	12	79
Equity-M14	SVI	Proportional Load Shed Reduction	3855	642	445	1574	1883	267	12	63

Table 5: **Summary of nominal load shed results across all combinations of EQUITY objective (group-level protections) and POLICY constraints when no budget is allocated for power line undergrounding.**

In Table 7, we observe that when there is no budget allocated, indigenous and Hispanic groups experience unfair load shedding outcomes across the board. When considering the baseline case (M1-BL), we see that indigenous and hispanic groups see about 2 and 1.4 times the average overall percent of load demanded that is shed, respectively. Asian and black communities experience disproportionately low levels of load shed, likely due to residence in urban areas with lower wildfire ignition risk, and low-income communities are also not at higher risk of experiencing load shed, again likely due to city poverty. If we set a 1% threshold as an "acceptable" percentage of load shed, we see that the overall population load shed is above this percentage threshold, and, in particular, uninsured, Hispanic, white, and indigenous groups are above this percentage threshold.

(a) **Nominal load shed in megawatt hours by group under only POLICY constraints when there is a $1 billion budget allocated for power line undergrounding.**

	Policy Constraint		Nominal Load Shed (MWh)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
M1 - BL	None	None	668	129	101	366	268	15	5.38	6.12
M2	Justice40	Proportional Budget Expenditure	718	141	103	372	313	13	5.92	6.05
M3	Justice40	Proportional Load Shed Reduction	919	161	119	443	432	17	7.79	9.83
M4	Justice40 (Modified)	Proportional Budget Expenditure	724	142	104	374	317	13	6.03	6.06
M5	Justice40 (Modified)	Proportional Load Shed Reduction	1662	311	236	746	743	119	7.14	21
M6	SVI	Proportional Budget Expenditure	748	147	104	392	321	15	6.54	6.21
M7	SVI	Proportional Load Shed Reduction	754	150	111	381	342	11	4.88	6.11

(b) **Nominal load shed in megawatt hours by group under under the EQUITY objective and POLICY constraints when there is a $1 billion budget allocated for power line undergrounding.**

	Policy Constraint		Nominal Load Shed (MWh)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
Equity-M8	None	None	1140	192	138	520	571	19	4.19	13
Equity-M9	Justice40	Proportional Budget Expenditure	1043	192	136	520	481	16	4.2	8.88
Equity-M10	Justice40	Proportional Load Shed Reduction	1488	221	188	545	654	163	4.4	57
Equity-M11	Justice40 (Modified)	Proportional Budget Expenditure	1155	208	151	534	559	33	4.31	9.73
Equity-M12	Justice40 (Modified)	Proportional Load Shed Reduction	2445	351	308	880	1056	264	7.1	93
Equity-M13	SVI	Proportional Budget Expenditure	1163	213	154	541	548	44	4.37	10
Equity-M14	SVI	Proportional Load Shed Reduction	1178	198	140	520	612	20	4.19	9.13

Table 6: **Summary of nominal load shed results across all combinations of EQUITY objective (group-level protections) and POLICY constraints when a $1 billion budget is allocated for power line undergrounding.**

Table 8 shows how these results change as we begin allocating budget for power line undergrounding. When we only consider policy constraints (Table 8a), we see that this small budget allocation decreases overall percent load shed by about 46%. Furthermore, with the exception of model M5,which is often an outlier, all groups except the indigenous group see their load shed percentage drop below the 1% threshold. White and Hispanic groups seem to experience the most benefit from this investment with over 50% reductions in percent of load demanded that is shed. Indigenous groups experience relatively less benefit, which is why the relative unfairness that they experience increases between the $0 and $250 million budgets when using only POLICY constraints. Now, we consider Table 8b where the EQUITY objective is incorporated. Relative to the POLICY-constraint only case in Table 8a and the

0-budget case in Table 7, relative unfairness decreases for both indigenous and Hispanic groups when we introduce the EQUITY objective. However, while relative unfairness is lower than that in the POLICY-constraint only case in Table 8a, the percent of load shed experienced is higher. For example, the overall load shed in Model M8 (EQUITY objective, no POLICY constraints), leads to only a 16% decrease in the percent of load demanded that is shed relative to the baseline model in the 0-budget case.

When budget increases to \$500 million, \$750 million, and eventually \$1 billion, indigenous load shed outcomes continue to be relatively unfair under POLICY constraints alone; even at the \$1 billion budget, Table 2a shows relative unfairness ratios for indigenous populations sometimes over 3 times that of the overall population. In contrast, unfairness ratios under the EQUITY objective are sub-2 as soon as a \$250 million budget is allocated. More importantly, by an allocation of \$500 million, indigenous percentage of load shed decreases relative to the baseline case, meaning that these groups are finally receiving real benefit from these investments *without pushing other groups' percent load shed above 1%.* This is why we argue that a MMF framework that minimizes the maximum percent of a group's load demanded that is shed coupled with a *sufficient* budget (in this case, at least \$500 million) allows for the controlling of wildfire risk *and* the fair reduction of load shed from emergency power shutoffs to all considered groups. When considering Tables 10 and the full results, shown in the main paper, these trends continue, lending more credence to this recommendation.

(a) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under only POLICY constraints when there is no budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Fairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Impoverished	Hispanic	White	Black	Indigenous	Asian
M1-BL	None	None	1.22 (1.0)	1.31 (1.07)	0.92 (0.75)	1.7 (1.39)	1.12 (0.92)	0.39 (0.32)	2.52 (2.07)	0.36 (0.3)
M2	Justice40	Proportional Budget Expenditure	1.22 (1.0)	1.32 (1.08)	0.92 (0.75)	1.7 (1.39)	1.12 (0.92)	0.38 (0.31)	2.52 (2.07)	0.35 (0.29)
M3	Justice40	Proportional Load Shed Reduction	1.22 (1.0)	1.32 (1.08)	0.92 (0.75)	1.71 (1.4)	1.12 (0.92)	0.38 (0.31)	2.5 (2.05)	0.35 (0.29)
M4	Justice40 (Modified)	Proportional Budget Expenditure	1.21 (1.0)	1.32 (1.09)	0.91 (0.75)	1.7 (1.4)	1.1 (0.91)	0.39 (0.32)	2.55 (2.11)	0.34 (0.28)
M5	Justice40 (Modified)	Proportional Load Shed Reduction	1.22 (1.0)	1.32 (1.08)	0.92 (0.75)	1.71 (1.4)	1.12 (0.92)	0.39 (0.32)	2.54 (2.08)	0.34 (0.28)
M6	SVI	Proportional Budget Expenditure	1.21 (1.0)	1.32 (1.09)	0.91 (0.75)	1.7 (1.4)	1.1 (0.91)	0.39 (0.32)	2.55 (2.11)	0.34 (0.28)
M7	SVI	Proportional Load Shed Reduction	1.21 (1.0)	1.32 (1.09)	0.91 (0.75)	1.7 (1.4)	1.11 (0.92)	0.38 (0.31)	2.51 (2.07)	0.36 (0.3)

(b) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under the EQUITY objective and POLICY constraints when there is no budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Fairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Impoverished	Hispanic	White	Black	Indigenous	Asian
Equity-M8	None	None	1.72 (1.0)	1.73 (1.01)	1.32 (0.77)	2.04 (1.19)	1.69 (0.98)	1.01 (0.59)	2.31 (1.34)	1.04 (0.6)
Equity-M9	Justice40	Proportional Budget Expenditure	1.84 (1.0)	1.77 (0.96)	1.38 (0.75)	2.05 (1.11)	1.98 (1.08)	0.88 (0.48)	2.31 (1.26)	1.04 (0.57)
Equity-M10	Justice40	Proportional Load Shed Reduction	1.63 (1.0)	1.66 (1.02)	1.26 (0.77)	2.06 (1.26)	1.64 (1.01)	0.59 (0.36)	2.31 (1.42)	0.6 (0.37)
Equity-M11	Justice40 (Modified)	Proportional Budget Expenditure	1.75 (1.0)	1.71 (0.98)	1.33 (0.76)	2.04 (1.17)	1.84 (1.05)	0.77 (0.44)	2.31 (1.32)	0.98 (0.56)
Equity-M12	Justice40 (Modified)	Proportional Load Shed Reduction	1.93 (1.0)	1.73 (0.9)	1.42 (0.74)	2.06 (1.07)	2.06 (1.07)	1.06 (0.55)	2.31 (1.2)	1.82 (0.94)
Equity-M13	SVI	Proportional Budget Expenditure	1.75 (1.0)	1.71 (0.98)	1.33 (0.76)	2.04 (1.17)	1.84 (1.05)	0.77 (0.44)	2.31 (1.32)	0.98 (0.56)
Equity-M14	SVI	Proportional Load Shed Reduction	1.87 (1.0)	1.83 (0.98)	1.46 (0.78)	2.05 (1.1)	2.02 (1.08)	1.13 (0.6)	2.31 (1.24)	0.77 (0.41)

Table 7: **Summary of load shed results across all combinations of EQUITY objective (group-level protections) and POLICY constraints when no budget is allocated.**

(a) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under only POLICY constraints when there is a $250 million budget allocated for power line undergrounding.**

	Policy Constraint: Vulnerability Index	Policy Constraint: Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
M1 - BL	None	None	0.66 (1.0)	0.75 (1.14)	0.59 (0.89)	**0.95 (1.44)**	0.61 (0.92)	0.12 (0.18)	**1.28 (1.94)**	0.15 (0.23)
M2	Justice40	Proportional Budget Expenditure	0.66 (1.0)	0.74 (1.12)	0.6 (0.91)	**0.95 (1.44)**	0.61 (0.92)	0.11 (0.17)	**1.66 (2.52)**	0.16 (0.24)
M3	Justice40	Proportional Load Shed Reduction	0.83 (1.0)	0.86 (1.04)	0.69 (0.83)	**1.09 (1.31)**	0.84 (1.01)	0.18 (0.22)	**1.78 (2.14)**	0.23 (0.28)
M4	Justice40 (Modified)	Proportional Budget Expenditure	0.66 (1.0)	0.74 (1.12)	0.6 (0.91)	**0.95 (1.44)**	0.61 (0.92)	0.11 (0.17)	**1.66 (2.52)**	0.16 (0.24)
M5	Justice40 (Modified)	Proportional Load Shed Reduction	1.07 (1.0)	1.16 (1.08)	0.79 (0.74)	**1.46 (1.36)**	1.01 (0.94)	0.36 (0.34)	**2.24 (2.09)**	0.35 (0.33)
M6	SVI	Proportional Budget Expenditure	0.66 (1.0)	0.74 (1.12)	0.6 (0.91)	**0.95 (1.44)**	0.61 (0.92)	0.11 (0.17)	**1.66 (2.52)**	0.16 (0.24)
M7	SVI	Proportional Load Shed Reduction	0.7 (1.0)	0.78 (1.11)	0.63 (0.9)	**0.97 (1.39)**	0.67 (0.96)	0.11 (0.16)	**1.66 (2.37)**	0.14 (0.2)

(b) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under the EQUITY objective and POLICY constraints when there is a $250 million budget allocated for power line undergrounding.**

	Policy Constraint: Vulnerability Index	Policy Constraint: Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
Equity-M8	None	None	1.02 (1.0)	0.95 (0.93)	0.83 (0.81)	1.14 (1.12)	1.14 (1.12)	0.3 (0.29)	1.29 (1.26)	0.5 (0.49)
Equity-M9	Justice40	Proportional Budget Expenditure	1.18 (1.0)	1.16 (0.98)	1.03 (0.87)	1.34 (1.14)	1.27 (1.08)	0.55 (0.47)	1.51 (1.28)	0.56 (0.47)
Equity-M10	Justice40	Proportional Load Shed Reduction	1.11 (1.0)	1.06 (0.95)	0.97 (0.87)	1.15 (1.04)	1.11 (1.0)	1.03 (0.93)	1.29 (1.16)	1.15 (1.04)
Equity-M11	Justice40 (Modified)	Proportional Budget Expenditure	1.19 (1.0)	1.14 (0.96)	1.03 (0.87)	1.33 (1.12)	1.26 (1.06)	0.58 (0.49)	1.51 (1.27)	0.87 (0.73)
Equity-M12	Justice40 (Modified)	Proportional Load Shed Reduction	1.47 (1.0)	1.27 (0.86)	1.17 (0.8)	1.43 (0.97)	1.43 (0.97)	1.43 (0.97)	1.6 (1.09)	1.43 (0.97)
Equity-M13	SVI	Proportional Budget Expenditure	1.22 (1.0)	1.18 (0.97)	1.07 (0.88)	1.34 (1.1)	1.34 (1.1)	0.6 (0.49)	1.51 (1.24)	0.51 (0.42)
Equity-M14	SVI	Proportional Load Shed Reduction	1.0 (1.0)	1.01 (1.01)	0.84 (0.84)	1.14 (1.14)	1.1 (1.1)	0.35 (0.35)	1.29 (1.29)	0.39 (0.39)

Table 8: **Summary of load shed results across all combinations of EQUITY objective (group-level protections) and POLICY constraints when a $250 million budget is allocated. The red, bolded text indicates "unfair" load shed, which we define as a group experiencing over 1.3 times the percent load shed that is experienced by the overall population. The red cells indicate load shed percentages above 1%.**

(a) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under only POLICY constraints when there is a $500 million budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Unfairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
M1 - BL	None	None	0.51 (1.0)	0.59 (1.16)	0.48 (0.94)	**0.71 (1.39)**	0.48 (0.94)	0.09 (0.18)	**1.23 (2.41)**	0.1 (0.2)
M2	Justice40	Proportional Budget Expenditure	0.53 (1.0)	0.59 (1.11)	0.5 (0.94)	**0.74 (1.4)**	0.5 (0.94)	0.09 (0.17)	**1.6 (3.02)**	0.12 (0.23)
M3	Justice40	Proportional Load Shed Reduction	0.67 (1.0)	0.71 (1.06)	0.59 (0.88)	**0.87 (1.3)**	0.68 (1.01)	0.15 (0.22)	**1.77 (2.64)**	0.24 (0.36)
M4	Justice40 (Modified)	Proportional Budget Expenditure	0.57 (1.0)	0.64 (1.12)	0.54 (0.95)	**0.79 (1.39)**	0.55 (0.96)	0.09 (0.16)	**1.6 (2.81)**	0.11 (0.19)
M5	Justice40 (Modified)	Proportional Load Shed Reduction	0.97 (1.0)	1.02 (1.05)	0.71 (0.73)	1.23 (1.27)	0.95 (0.98)	0.35 (0.36)	**1.83 (1.89)**	0.5 (0.52)
M6	SVI	Proportional Budget Expenditure	0.53 (1.0)	0.6 (1.13)	0.52 (0.98)	**0.74 (1.4)**	0.51 (0.96)	0.08 (0.15)	**1.54 (2.91)**	0.1 (0.19)
M7	SVI	Proportional Load Shed Reduction	0.53 (1.0)	0.61 (1.15)	0.49 (0.92)	**0.73 (1.38)**	0.51 (0.96)	0.09 (0.17)	**1.29 (2.43)**	0.12 (0.23)

(b) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under the EQUITY objective and POLICY constraints when there is a $500 million budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Unfairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
Equity-M8	None	None	0.75 (1.0)	0.76 (1.01)	0.63 (0.84)	0.91 (1.21)	0.79 (1.05)	0.22 (0.29)	**1.03 (1.37)**	0.34 (0.45)
Equity-M9	Justice40	Proportional Budget Expenditure	0.71 (1.0)	0.78 (1.1)	0.64 (0.9)	**0.98 (1.38)**	0.66 (0.93)	0.17 (0.24)	**1.11 (1.56)**	0.2 (0.28)
Equity-M10	Justice40	Proportional Load Shed Reduction	0.94 (1.0)	0.86 (0.91)	0.78 (0.83)	0.93 (0.99)	0.93 (0.99)	0.93 (0.99)	1.04 (1.11)	0.93 (0.99)
Equity-M11	Justice40 (Modified)	Proportional Budget Expenditure	0.88 (1.0)	0.83 (0.94)	0.69 (0.78)	1.01 (1.15)	0.98 (1.11)	0.21 (0.24)	1.13 (1.28)	0.4 (0.45)
Equity-M12	Justice40 (Modified)	Proportional Load Shed Reduction	1.35 (1.0)	1.13 (0.84)	1.11 (0.82)	1.3 (0.96)	1.29 (0.96)	1.3 (0.96)	1.45 (1.07)	1.3 (0.96)
Equity-M13	SVI	Proportional Budget Expenditure	0.8 (1.0)	0.84 (1.05)	0.68 (0.85)	1.0 (1.25)	0.82 (1.02)	0.22 (0.27)	**1.13 (1.41)**	0.29 (0.36)
Equity-M14	SVI	Proportional Load Shed Reduction	0.82 (1.0)	0.79 (0.96)	0.7 (0.85)	0.91 (1.11)	0.91 (1.11)	0.31 (0.38)	1.03 (1.26)	0.51 (0.62)

Table 9: **Summary of load shed results across all combinations of EQUITY objective (group-level protections) and POLICY constraints when a $500 million budget is allocated. The red, bolded text indicates "unfair" load shed, which we define as a group experiencing over 1.3 times the percent load shed that is experienced by the overall population. The red cells indicate load shed percentages above 1%.**

(a) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under only POLICY constraints when there is a $750 million budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Unfairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Low-Income	Hispanic	White	Black	Indigenous	Asian
M1 - BL	None	None	0.4 (1.0)	0.47 (1.17)	0.4 (1.0)	**0.56 (1.4)**	0.38 (0.95)	0.08 (0.2)	**1.17 (2.92)**	0.08 (0.2)
M2	Justice40	Proportional Budget Expenditure	0.44 (1.0)	0.51 (1.16)	0.42 (0.95)	**0.62 (1.41)**	0.42 (0.95)	0.09 (0.2)	**1.23 (2.8)**	0.09 (0.2)
M3	Justice40	Proportional Load Shed Reduction	0.55 (1.0)	0.56 (1.02)	0.45 (0.82)	**0.73 (1.33)**	0.55 (1.0)	0.1 (0.18)	**1.46 (2.65)**	0.2 (0.36)
M4	Justice40 (Modified)	Proportional Budget Expenditure	0.45 (1.0)	0.51 (1.13)	0.42 (0.93)	**0.61 (1.36)**	0.44 (0.98)	0.07 (0.16)	**1.14 (2.53)**	0.1 (0.22)
M5	Justice40 (Modified)	Proportional Load Shed Reduction	0.84 (1.0)	0.87 (1.04)	0.62 (0.74)	1.06 (1.26)	0.88 (1.05)	0.24 (0.29)	**1.57 (1.87)**	0.29 (0.35)
M6	SVI	Proportional Budget Expenditure	0.45 (1.0)	0.53 (1.18)	0.43 (0.96)	**0.62 (1.38)**	0.43 (0.96)	0.08 (0.18)	**1.18 (2.62)**	0.08 (0.18)
M7	SVI	Proportional Load Shed Reduction	0.44 (1.0)	0.51 (1.16)	0.41 (0.93)	**0.61 (1.39)**	0.43 (0.98)	0.07 (0.16)	**1.08 (2.45)**	0.09 (0.2)

(b) **Percent of load demanded that is shed and relative unfairness in the percent of load demanded that is shed by group under the EQUITY objective and POLICY constraints when there is a $750 million budget allocated for power line undergrounding.**

	Policy Constraint		Percent of Load Demanded That is Shed (Relative Fairness)							
	Vulnerability Index	Constraint Type	Overall	Uninsured	Impoverished	Hispanic	White	Black	Indigenous	Asian
Equity-M8	None	None	0.59 (1.0)	0.62 (1.05)	0.51 (0.86)	0.75 (1.27)	0.63 (1.07)	0.09 (0.15)	**0.84 (1.42)**	0.13 (0.22)
Equity-M9	Justice40	Proportional Budget Expenditure	0.62 (1.0)	0.65 (1.05)	0.53 (0.85)	0.8 (1.29)	0.64 (1.03)	0.1 (0.16)	**0.89 (1.44)**	0.15 (0.24)
Equity-M10	Justice40	Proportional Load Shed Reduction	0.84 (1.0)	0.72 (0.86)	0.66 (0.79)	0.82 (0.98)	0.82 (0.98)	0.82 (0.98)	0.92 (1.1)	0.82 (0.98)
Equity-M11	Justice40 (Modified)	Proportional Budget Expenditure	0.69 (1.0)	0.67 (0.97)	0.55 (0.8)	0.8 (1.16)	0.77 (1.12)	0.15 (0.22)	0.89 (1.29)	0.21 (0.3)
Equity-M12	Justice40 (Modified)	Proportional Load Shed Reduction	1.25 (1.0)	1.06 (0.85)	1.03 (0.82)	1.2 (0.96)	1.2 (0.96)	1.2 (0.96)	1.34 (1.07)	1.21 (0.97)
Equity-M13	SVI	Proportional Budget Expenditure	0.72 (1.0)	0.71 (0.99)	0.59 (0.82)	0.82 (1.14)	0.79 (1.1)	0.19 (0.26)	0.92 (1.28)	0.36 (0.5)
Equity-M14	SVI	Proportional Load Shed Reduction	0.65 (1.0)	0.64 (0.98)	0.51 (0.78)	0.75 (1.15)	0.76 (1.17)	0.09 (0.14)	0.84 (1.29)	0.12 (0.18)

Table 10: **Summary of load shed results across all combinations of EQUITY objective (group-level protections) and POLICY constraints when a $750 million budget is allocated. The red, bolded text indicates "unfair" load shed, which we define as a group experiencing over 1.3 times the percent load shed that is experienced by the overall population. The red cells indicate load shed percentages above 1%.**