Power Shutoff Amidst Wildfire Risks in San Diego City

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1. Introduction

Wildfires pose a significant threat to both natural and human-made environment, and electric power infrastructures have been identified as a potential ignition source. This issue strikes a critical balance between maintaining uninterrupted power supply to support economic and social activities, and mitigating the wildfire risks that power system may pose during hazardous conditions. Power lines have caused more than 4,000 wildfires in Texas from 2010 to 2014, and power lines can ignite wildfires through a variety of mechanisms such as vegetation contact with high-voltage power lines [1]. This research focuses on a preventive approach that strategically scheduling generator shutoffs within the power grid to mitigate the wildfire risks. We examine this issue by zoning in on the specific sub-regions classified by zip codes and analyzing hourly generator shutoffs.

1.1 Problem Statement

The primary objective of this research is to plan hourly power shutoffs in the city of San Diego in California state to minimize the risk of wildfires, together with the total dis-utility, namely the amount of electricity demand lost due to the power shutoff; and in addition to that, to maintain equitable treatment across different sub-regions. The decision-making process involves determining the optimal number of generators to deactivate during specific periods to balance the risk of wildfires with the need for electricity.

2. Literature Review

In the context of operational strategies for electric utilities, the paper "Balancing Wildfire Risk and Power Outages through Optimized Power Shut-Offs" proposes an optimization model targeting the dual objectives of wildfire risk minimization and power delivery maximization [6]. Unlike this model, which encompasses buses, generators, and transmission lines, our research specifically focuses on the generators within sub-regions. This differentiation arises from the unique data constraints we face, as our model does not include detailed information about how lines interconnect buses and generators.

Furthermore, while Rhodes et al. maintain a uniform importance metric across regions [6], we were able to calculate a differential importance metric that reflects the severity of impact of power outages in each sub-region, as indicated by the number of important infrastructures. Our approach differentiates the impact of power outages on the objective function based on the density of critical infrastructure within each sub-region. This approach allows us to finely tune the model to San Diego's unique infrastructure needs that prioritizes power delivery to essential services and thereby enhance the model's sensitivity to the societal implications of electricity loss. Our research expands upon the foundations laid by Rhodes et al. by refining the assessment of regional importance and adapting the model to a data-specific scenario. This comparison underscores the flexibility required in adapting wildfire risk mitigation strategies to different environmental and infrastructural conditions.

Taylor et al. present the California Test System (CATS), a geographically accurate synthetic model of California's grid, which we utilize extensively for its detailed representation of generators, buses, and transmission lines [7]. This dataset forms the backbone of our analysis that enables a comprehensive examination of the San Diego region's power system under various operational scenarios.

Lastly, the paper "Distribution System Operation Amidst Wildfire-Prone Climate Conditions Under Decision-Dependent Line Availability Uncertainty" presents a novel optimization model for power system operations to minimize wildfire risks through strategic grid adjustments [3]. This model incorporates decision-dependent uncertainties to adapt network topology, particularly by switching actions that alter line flows, thus reducing the likelihood of line failures that could lead to wildfires [3]. In contrast, we choose not to alter the physical network but to directly control the switch of generators. This distinction emphasizes our project's adaptation to the available data and operational constraints specific to the local grid infrastructure. Despite not being able to optimize both the pre-contingency and worst-case post-contingency operations due to the need for intricate formulations for an ambiguity set and taking expectations, we still harvested a great amount of inspiration from this paper. And this will serve as our goal for future improvement.

In summary, we build upon established models to devise a strategy that reflects the dynamics of San Diego's power system. We aim to minimize the combined impact of wildfire risk and energy dis-utility. By applying constraints, we ensure fairness in electricity distribution and maintain risk at acceptable levels.

3. Method

(3.1) Assumptions

Based on the modeling and data from CATS and Cal-Adapt, we proposed the following assumptions:

(1) Every sub-region is assumed to be serviced by at least one power generator.

(2) Within each sub-region, the generators serves as the exclusive source of power to ensure that all energy requirements are met solely through these facilities.

(3) Within each sub-region, the generators exclusively supply power to meet the demand of that specific sub-region, without transferring energy to or from adjacent sub-regions.

(4) The output capacity of all generators within a single sub-region is assumed equivalent.

(5) Each generator's risk contribution to potential wildfire ignition is assumed uniform across a sub-region, allowing for a balanced assessment of risk.

(6) The probability of wildfire occurrence is constant for each sub-region throughout the all time periods in a day.

(7) The power demand fluctuation between each time period within each sub-region is assumed to follow a fixed trend.

(8) Baseline risk for wildfire occurrences in each sub-region is set at 20% of the calculated wildfire probability to account for inherent environmental and operational risks.

(9) Assume no transmission losses within sub-regions and efficient power delivery from generators to consumers.

(3.2) Sets and Parameters:

- I: The set of sub-regions (Zipcode).
- G_i: The set of generators in sub-region i.
- T: Hours within a day.
- J_i: Number of generators in sub-region i.

- p_i: The probability of a wildfire occurring at sub-region i.
- E_i: The average hourly demand for electricity in kilowatt-hour in sub-region i.
- w_i: Metric indicating the importance of a sub-region i.
- τ_t: The factor that adjust demand depending on the time of the day t.
- α: Parameter that balances the trade-off.

(3.3) Decision variable:

- $z_{i,j,t}$, indicates whether generator j in sub-region i is open at time t
- $no\_gen\_on_{i,t}$, indicates whether no generators are operating for sub-region i at time t.

(3.4) Model:

To describe in plain words, our objective is to minimize total wildfire probability and lost demand. By incorporating the convex combination parameter to denote the trade-off, we obtain:

$$\min(\alpha \cdot \text{Wildfire probability} + (1-\alpha) \cdot \text{dis-utility}),$$

which, according to our assumption (4 - 7), is equal to:

$$\min \sum_{i \in I} \sum_{t \in T} \alpha R_i * \frac{openG}{totalG} + (1-\alpha) Weight_i * Demand_{i,t} * \frac{openG}{totalG}$$

Substituting in the previously defined sets and parameters, we get

$$\min \sum_{i \in I} \sum_{t \in T} \left(\alpha \cdot p_i \cdot \left(\frac{\sum_{j=1}^{J_i} z_{i,j,t}}{J_i} \right) + (1-\alpha) \cdot E_i \cdot w_i \cdot \tau_t \cdot \left(1 - \frac{\sum_{j=1}^{J_i} z_{i,j,t}}{J_i} \right) \right) \tag{1}$$

(3.5) Constraints:

- **Constraint on upper bound of acceptable wildfire risk level:**

$$\sum_{t \in T} \left(0.2 \cdot p_i + 0.8 \cdot p_i \cdot \frac{\sum_{j \in G_i} z_{i,j,t}}{J_i} \right) \leq 0.8 \cdot 24 \cdot p_i, \quad \forall i \in I \tag{2}$$

The cumulative risk is controlled by constraining the sum of the risk across all time periods. This approach is a linear approximation of the product of risks, which Gurobi cannot solve directly due to its non-linear nature. By ensuring that the aggregate risk does not exceed 80% of the baseline risk over a 24-hour period, we implicitly reduce the compounded risk. Although 0.8 seems like a high fraction, it is justifiable considering that the actual risk aggregation is multiplicative, and the control over the sum of individual risks ensures that the product, or cumulative risk, remains within a safe range.

- **Limiting Non-Operational Hours:**

To mitigate the impact of power shortages on critical services and everyday life, we enforce a limit on the number of hours that generators can remain non-operational within a single day. This constraint is applied to all sub-regions that have at least one generator. The mathematical representation is:

$$\sum_{t \in T} \text{no\_gen\_on}_{i,t} \leq 6, \quad \forall i \in I \text{ with } J_i > 0. \tag{3}$$

This signifies that for any sub-region i, there cannot be more than 6 hours in a day when all generators are off. This threshold is chosen to provide a balance between the need for downtime of generators and to keep the electricity supply consistent.

- **Activation of the indicator: no_gen_on:**

$$\text{no\_gen\_on}_{i,t} = 1 \quad \text{if } \sum_{j=1}^{J_i} z_{i,j,t} = 0, \forall i \in I, t \in T$$

$$\text{no\_gen\_on}_{i,t} = 0 \quad \text{if } \sum_{j=1}^{J_i} z_{i,j,t} \geq 1, \forall i \in I, t \in T$$

This means that if no generators are running in sub-region i at time t, then $\text{no\_gen\_on}_{i,t}$ is set to 1. Conversely, if at least one generator is operational, $\text{no\_gen\_on}_{i,t}$ is set to 0.

- **Fairness constraint:**
To ensure equity in the distribution of electricity, we impose a variance constraint on service interruptions:

$$\text{Var}\{\sum_{t \in T}(1 - \frac{\sum_{j \in G_i} z_{i,j,t}}{J_i}) \mid i \in I\} \leq 10$$

Here, $\text{Var}(\cdot)$ denotes the variance, and the expression inside the variance measures the sum of the fraction of non-operating generators across all time periods. A smaller variance ensures that no sub-region disproportionately bears the burden of power outages, thereby promoting fairness. We chose 10 as the acceptable level of disparity among the sub-regions. This constraint ensures that all sub-regions receive a similar level of service reduction, yet any discrimination still remains justified by the region's power consumption level and importance metric.

4. Experimental Design

(4.1) Data

Our research utilizes comprehensive datasets associated with power system operations in San Diego. These datasets include:

- **Zip Code:** We employ geographic data segmented by zip codes to pinpoint specific areas within San Diego. This allows for a detailed spatial analysis of power distribution and risk areas.
- **Generator:** Data on power generators includes geographical location. This information is crucial for modeling potential power flow disruptions and planning strategic shutoffs. The relevant data is extracted from CATS [7]. Figure 1 shows the distribution of generators in San Diego city within each sub-region.

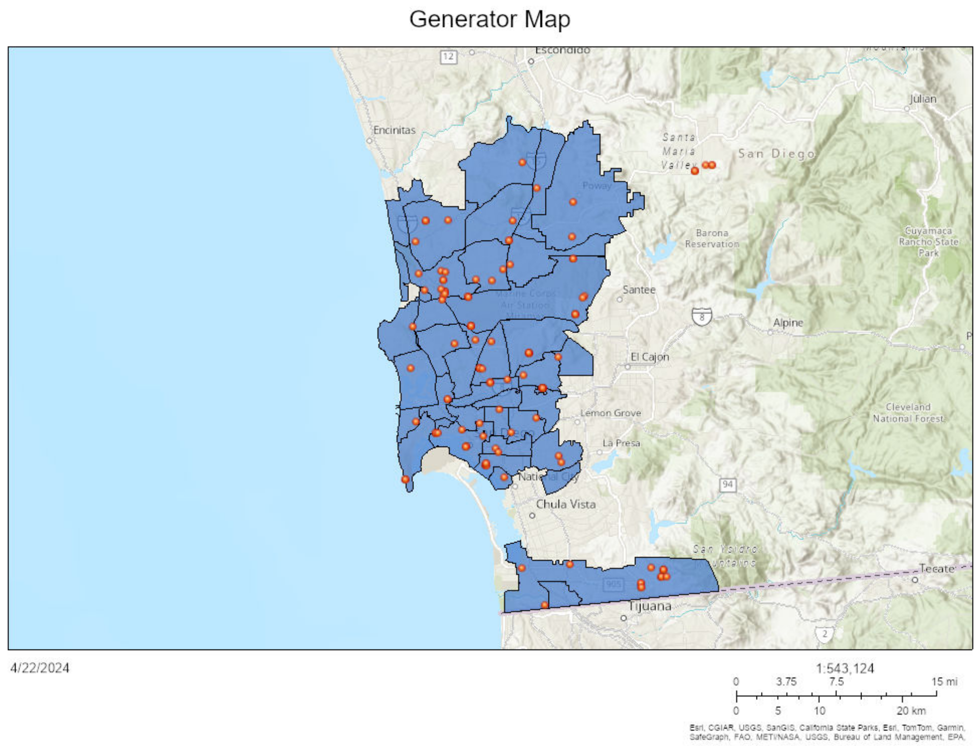

Figure 1: Generator Map in San Diego

- **Risk:** Risk assessment data encompasses historical wildfire occurrences and predictive modeling outcomes. In our analysis, we considered the "Decadal wildfire probability" from Cal-Adapt to estimate the probability of wildfires for the current decade, aligning with our project's time frame. We chose the medium scenario (RCP 4.5), which presumes a peak in emissions around 2040 before a decline, and selected the CanESM2 (Average) model for its representation of an average-case climate projection. These choices are intended to provide a balanced view of future risks, which takes into account the moderate yet realistic scenarios of climate and wildfire probabilities [2], [8]. We then extracted the probabilities of wildfire for each sub-region using their geographical boundary data.
- **Infrastructure:** We catalog critical infrastructure such as hospitals, schools, transition stops, and colleges within the power grid. This data is used to assess the impact of power outages on essential services and prioritize maintenance and protection efforts [4]. Figure 2 shows the distribution of different types of infrastructures. Yellow dots are educational infrastructure and orange dots are hospitals. Other infrastructures are not displayed due to geographical overlapping.
- **Hourly Power Consumption Factor:** We account for variations in daily power demand by introducing a time-dependent adjustment factor, τ_t, which scales the demand based on the time of day t. This factor is calibrated with the power demand at 12 pm serving as a baseline. Typically, demand is lowest overnight, gradually increases as people wake up, continues increasing during the office hours, and reaches its peak at around 1.2 times of that at noon in the evening as households activate more appliances [5]. Figure 3 shows the fluctuation of hourly power consumption in MWH averaged over 5 years from 2014 to 2018 in San Diego [5].

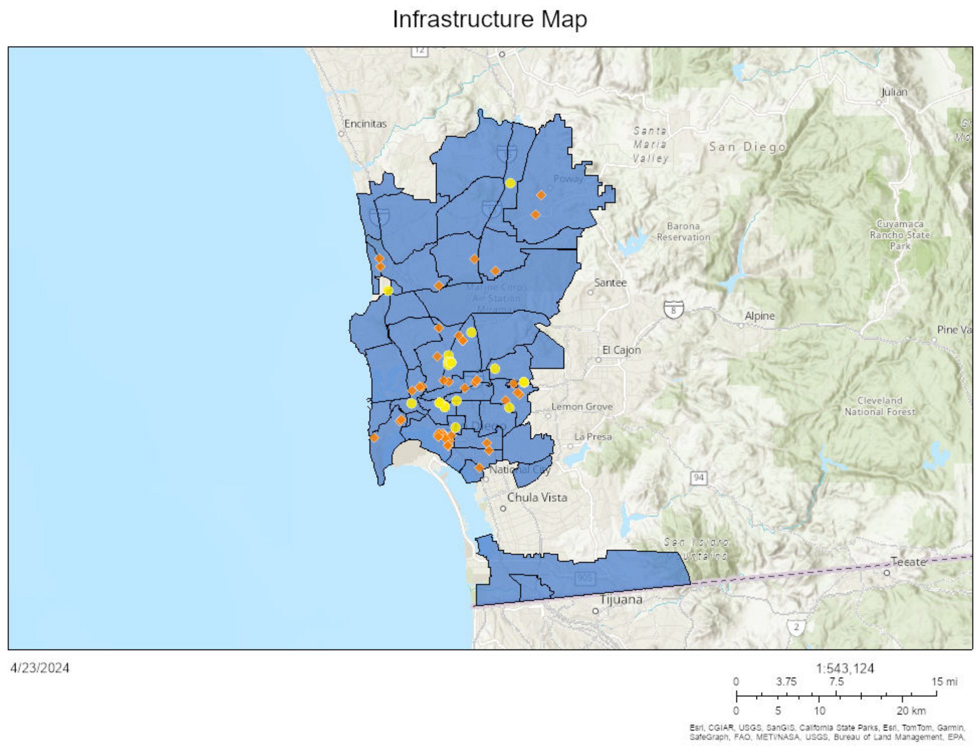

Figure 2: Infrastructure

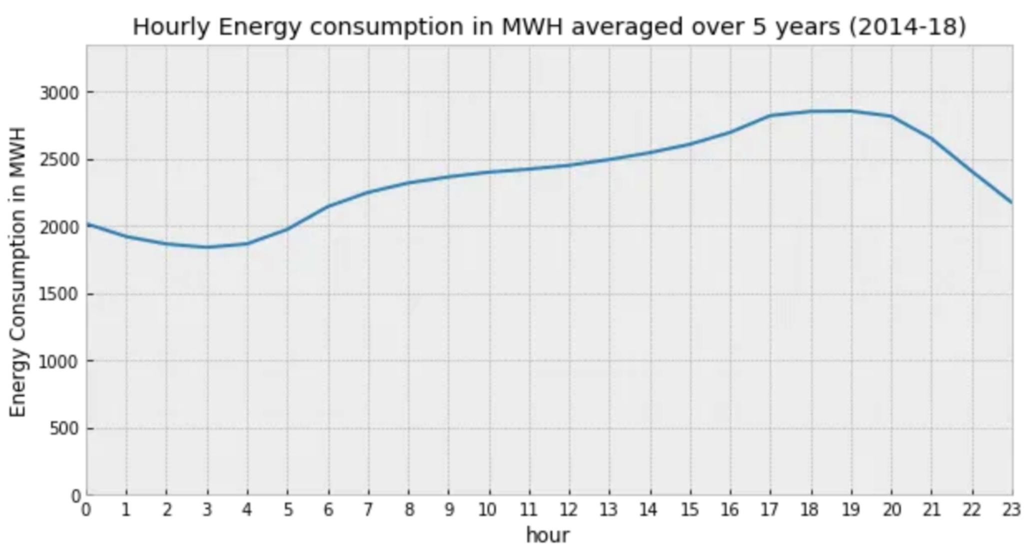

Figure 3: Hourly Energy Consumption in MWH averaged over 5 years 2014 - 18

(4.2) CPU Time: The model is solved in Python using the Gurobi optimizer on a machine with a 1.4 GHz Quad-Core Intel Core i5 CPU and 8 GB of memory. With this, the optimal power shut-off optimization problem solves in less than 0.5s.

(4.3) Choice of Parameters:

- **Baseline Risk:** The baseline risk for each region is set at 20% of the original wildfire probability, denoted by $0.2 \cdot p_i$ for region i. This value is selected to account for the inherent risk of wildfires that exists independently of generator operations. Even in the absence of any generator activity, external factors such as environmental conditions, human activities, and other sources of ignition can still contribute to risk of inciting a wildfire. Therefore, this baseline risk ensures that the model captures a realistic level of unavoidable risk.

- **Trade-off parameter α:** To determine an optimal value of the convex combination parameter α, we plotted the efficiency frontier, as illustrated in the graph below. This depicts the trade-off between total dis-utility and risk. Each point on the curve corresponds to a different value of the parameter α. The risk is multiplied by 10000 to bring it to a comparable scale with the dis-utility term. This scaling is necessary to visualize the impact of α on both risk and dis-utility in a single coherent framework.

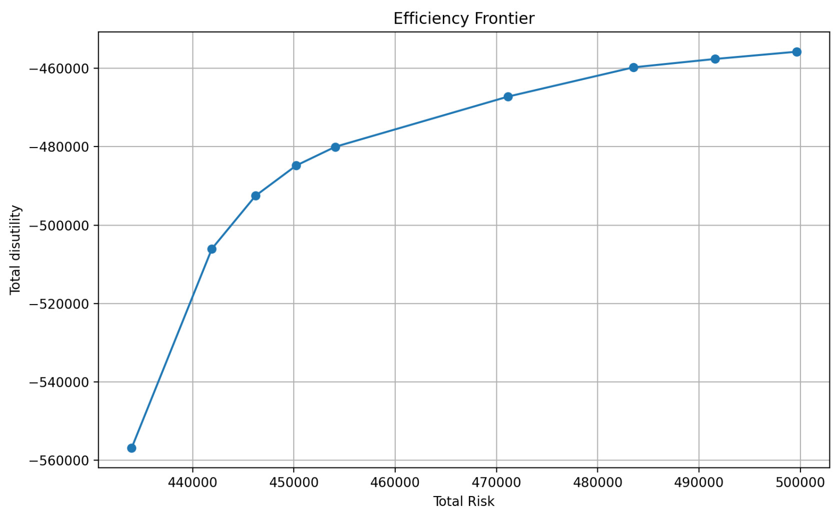

Figure 4: Efficiency Frontier showing the trade-off between total dis-utility and scaled risk for α from 0.1 to 0.9.

As α increases, the emphasis on minimizing risk over dis-utility grows, shifting the balance point on the frontier upwards. Conversely, a lower α prioritizes minimizing dis-utility. The frontier enables us to select an α that aligns with our operational objectives.

The selection of $\alpha = 0.5$ corresponds to a gradient of 1.24 on the efficiency frontier, indicating a near-equitable trade-off between wildfire risk and dis-utility, with a slight preference for risk reduction. To further investigate the point where gradient is closer to 1, we magnified the portion ranging from $\alpha = 0.4$ to $\alpha = 0.51$ to experiment with a finer granularity. Result is demonstrated in the following figure.

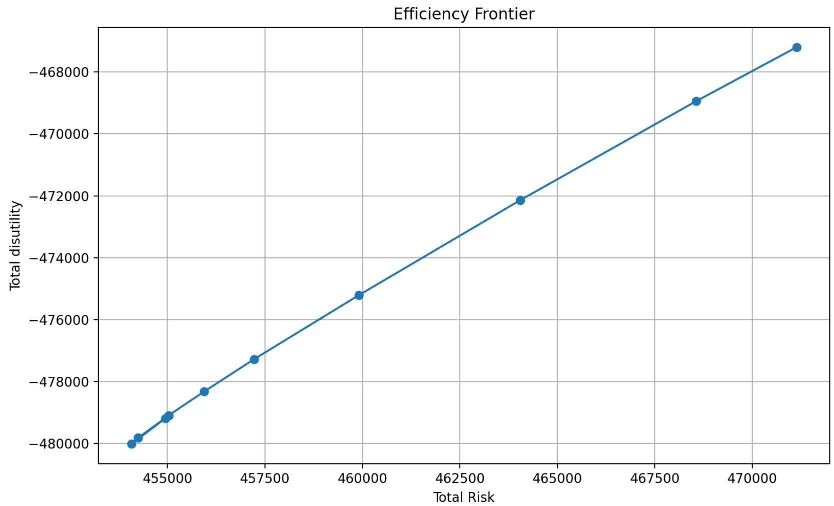

Figure 5: Efficiency Frontier from $\alpha = 0.4$ to $\alpha = 0.51$.

Computation results show that $\alpha = 0.49$ yields a gradient $= 0.953$. Choosing this α value aligns with the principle of diminishing returns, where beyond a certain point, efforts to further reduce risk result in a disproportionate increase in dis-utility. By choosing $\alpha = 0.49$, we achieve a rational compromise between the two objectives, before hitting the flat part of the curve, where additional dis-utility reduction becomes significantly more costly in terms of risk.

- **Variance Limit:** The variance limit in is set at 10. The value is selected as a result from running the sensitivity analysis for α on various different variance limits, ranging from 1 to 100. For too large limits, the constraint ends up being of little use to promoting fairness among power distribution, whereas for too small limits, we observed the constraint imposing too strict conditions, to the extent at which kinks shows up between adjacentα values on the efficiency frontier. And gradient occasionally takes on infinite values, likely inferring that our objective function is being trivialized due to too strict fairness constraints.

5. Conclusion

This study presents an analysis of generator operational strategies in various sub-regions divided based on zipcodes to manage electricity demand and minimize wildfire risks in the city of San Diego. By assessing the number of functional generators and computing the risk and dis-utility metrics across multiple time periods throughout a day, we provide insights into how strategic planning can enhance efficiency and mitigate ignition risks in electricity distribution. These findings provide valuable insights for decision-makers and stakeholders who are seeking to optimize electricity supply operations, or who simply cares about balancing safety and efficiency in power distribution. In this section, we present the numerical results obtained from running the model we established in above sections in the Gurobi software.

Hour	Generators Open	Hour	Generators Open
0	4.0	12	4.0
1	4.0	13	4.0
2	4.0	14	4.0
3	1.0	15	4.0
4	0.0	16	4.0
5	0.0	17	4.0
6	0.0	18	4.0
7	0.0	19	4.0
8	0.0	20	4.0
9	3.0	21	4.0
10	4.0	22	4.0
11	4.0	23	4.0

Table 1: Hourly Status of Generators Open in Zip Code 92130

The table above illustrates the hourly operational status of generators in Zipcode 92130. Notably, all four generators are on during peak hours from 10 AM to 11 PM, which is consistent with anticipated peak electricity demand periods. This operational pattern is reasonable, as energy consumption typically escalates during these hours due to residential, commercial, and industrial activities. The reduction in generator operation during the early morning hours (from 3 AM to 8 AM) reflects lower energy demand.

Column Set 1			Column Set 2		
ZipCode	Risk	dis-utility	ZipCode	Risk	dis-utility
92014	0.605951	35790.693	92106	0.351976	10775.412
92037	0.446562	36687.977	92107	0.310018	24769.467
92064	2.345737	308304.659	92108	1.093060	165802.218
92065	3.276269	87077.969	92109	0.465371	36107.659
92101	0.418303	152340.211	92110	0.640417	20204.697
92102	0.427798	41435.250	92111	0.968636	112335.751
92103	0.480313	67992.216	92113	0.456061	12446.280
92104	0.905601	28766.644	92114	0.399684	17021.153
92105	0.948596	21339.272	92115	0.588371	278602.503
92116	1.037553	45641.171	92117	0.887284	33705.529
92119	2.967847	20484.786	92120	2.699127	40711.002
92121	1.035618	39416.882	92122	0.874744	50279.982
92123	2.274811	137643.836	92124	1.222309	58771.872
92126	1.974952	111926.836	92127	2.094224	65885.863
92128	2.819392	93261.889	92129	1.616751	44189.908
92130	1.053118	119999.496	92131	3.005275	99408.693
92139	0.341993	20974.332	92154	2.215860	219324.899
92173	0.306507	75430.831			
Total Risk: 43.556			**Total dis-utility: 2734857.839**		

Table 2: Summary of risk and dis-utility for various regions

The table above provides a detailed summary of risk and dis-utility metrics across all sub-regions. Risk here is defined as the aggregated wildfire probabilities across all time periods resulting from generator operational decisions. dis-utility, measured in kWh, quantifies the lost demand across all time periods due to these shutdowns.

The zipcode 92064 records the highest dis-utility at 308304.659. This is reasonable considering its low importance metric (0.0333), high expected power consumption (24828.939 kWh per hour), and significant wildfire risk (17.8%). These factors justify the high dis-utility, as substantial measures are required to manage the significant risk in this region with lower infrastructure importance.

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Appendix

Hour	Open G.	Hour	Open G.
0	2.0	12	2.0
1	2.0	13	2.0
2	2.0	14	2.0
3	0.0	15	2.0
4	0.0	16	2.0
5	0.0	17	2.0
6	0.0	18	2.0
7	0.0	19	2.0
8	0.0	20	2.0
9	2.0	21	2.0
10	2.0	22	2.0
11	2.0	23	2.0

Hourly Status of Generators Open in Zip Code 92037

Hour	Open G.	Hour	Open G.
0	1	12	1.0
1	1.0	13	5.0
2	0.0	14	5.0
3	0.0	15	5.0
4	0.0	16	5.0
5	0.0	17	5.0
6	0.0	18	5.0
7	0.0	19	5.0
8	0.0	20	5.0
9	0.0	21	5.0
10	0.0	22	5.0
11	0.0	23	5.0

Hourly Status of Generators Open in Zip Code 92065

Hour	Open G.	Hour	Open G.
0	0.0	12	0.0
1	0.0	13	0.0
2	0.0	14	0.0
3	0.0	15	0.0
4	0.0	16	0.0
5	0.0	17	0.0
6	0.0	18	0.0
7	0.0	19	0.0
8	0.0	20	0.0
9	0.0	21	0.0
10	0.0	22	0.0
11	0.0	23	0.0

Hourly Status of Generators Open in Zip Code 92173

Hour	Open G.	Hour	Open G.
0	5.0	12	5.0
1	5.0	13	5.0
2	5.0	14	5.0
3	0.0	15	5.0
4	0.0	16	5.0
5	0.0	17	5.0
6	0.0	18	5.0
7	0.0	19	5.0
8	0.0	20	5.0
9	5.0	21	5.0
10	5.0	22	5.0
11	5.0	23	5.0

Hourly Status of Generators Open in Zip Code 92101

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	0.0	14	1.0
3	0.0	15	2.0
4	0.0	16	2.0
5	0.0	17	2.0
6	0.0	18	2.0
7	0.0	19	2.0
8	0.0	20	2.0
9	0.0	21	2.0
10	0.0	22	1.0
11	0.0	23	1.0

Hourly Status of Generators Open in Zip Code 92064

Hour	Open G.	Hour	Open G.
0	2.0	12	2.0
1	2.0	13	2.0
2	2.0	14	2.0
3	0.0	15	2.0
4	0.0	16	2.0
5	0.0	17	2.0
6	0.0	18	2.0
7	0.0	19	2.0
8	0.0	20	2.0
9	2.0	21	2.0
10	2.0	22	2.0
11	2.0	23	2.0

Hourly Status of Generators Open in Zip Code 92102

Hour	Open G.	Hour	Open G.
0	0.0	12	0.0
1	0.0	13	0.0
2	0.0	14	0.0
3	0.0	15	0.0
4	0.0	16	0.0
5	0.0	17	0.0
6	0.0	18	0.0
7	0.0	19	0.0
8	0.0	20	0.0
9	0.0	21	0.0
10	0.0	22	0.0
11	0.0	23	0.0

Hourly Status of Generators Open in Zip Code 92103

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	1.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92104

Hour	Open G.	Hour	Open G.
0	2.0	12	2.0
1	2.0	13	2.0
2	2.0	14	2.0
3	2.0	15	2.0
4	0.0	16	2.0
5	0.0	17	2.0
6	0.0	18	2.0
7	0.0	19	2.0
8	0.0	20	2.0
9	0.0	21	2.0
10	2.0	22	2.0
11	2.0	23	2.0

Hourly Status of Generators Open in Zip Code 92105

Hour	Open G.	Hour	Open G.
0	3.0	12	3.0
1	3.0	13	3.0
2	3.0	14	3.0
3	0.0	15	3.0
4	0.0	16	3.0
5	0.0	17	3.0
6	0.0	18	3.0
7	0.0	19	3.0
8	0.0	20	3.0
9	3.0	21	3.0
10	3.0	22	3.0
11	3.0	23	3.0

Hourly Status of Generators Open in Zip Code 92106

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92107

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	1.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92108

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	1.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92109

Hour	Open G.	Hour	Open G.
0	6.0	12	6.0
1	6.0	13	6.0
2	6.0	14	6.0
3	0.0	15	6.0
4	0.0	16	6.0
5	0.0	17	6.0
6	0.0	18	6.0
7	0.0	19	6.0
8	0.0	20	6.0
9	6.0	21	6.0
10	6.0	22	6.0
11	6.0	23	6.0

Hourly Status of Generators Open in Zip Code 92113

Hour	Open G.	Hour	Open G.
0	2.0	12	2.0
1	2.0	13	2.0
2	2.0	14	2.0
3	0.0	15	2.0
4	0.0	16	2.0
5	0.0	17	2.0
6	0.0	18	2.0
7	0.0	19	2.0
8	0.0	20	2.0
9	2.0	21	2.0
10	2.0	22	2.0
11	2.0	23	2.0

Hourly Status of Generators Open in Zip Code 92110

Hour	Open G.	Hour	Open G.
0	2.0	12	2.0
1	2.0	13	2.0
2	2.0	14	2.0
3	0.0	15	2.0
4	0.0	16	2.0
5	0.0	17	2.0
6	0.0	18	2.0
7	0.0	19	2.0
8	0.0	20	2.0
9	2.0	21	2.0
10	2.0	22	2.0
11	2.0	23	2.0

Hourly Status of Generators Open in Zip Code 92114

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	1.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92111

Hour	Open G.	Hour	Open G.
0	0	12	0
1	0	13	0
2	0	14	0
3	0	15	0
4	0	16	0
5	0	17	0
6	0	18	0
7	0	19	0
8	0	20	0
9	0	21	0
10	0	22	0
11	0	23	0

Hourly Status of Generators Open in Zip Code 92115

Hour	Open G.	Hour	Open G.
0	0	12	0
1	0	13	0
2	0	14	0
3	0	15	0
4	0	16	0
5	0	17	0
6	0	18	0
7	0	19	0
8	0	20	0
9	0	21	0
10	0	22	0
11	0	23	0

Hourly Status of Generators Open in Zip Code 92116

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	0.0	13	1.0
2	0.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	0.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92120

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	1.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92117

Hour	Open G.	Hour	Open G.
0	14.0	12	14.0
1	14.0	13	14.0
2	14.0	14	14.0
3	0.0	15	14.0
4	0.0	16	14.0
5	0.0	17	14.0
6	0.0	18	14.0
7	0.0	19	14.0
8	0.0	20	14.0
9	14.0	21	14.0
10	14.0	22	14.0
11	14.0	23	14.0

Hourly Status of Generators Open in Zip Code 92121

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	0.0	13	1.0
2	0.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	0.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92119

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	1.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92122

Hour	Open G.	Hour	Open G.
0	9.0	12	9.0
1	9.0	13	9.0
2	9.0	14	9.0
3	9.0	15	9.0
4	0.0	16	9.0
5	0.0	17	9.0
6	0.0	18	9.0
7	0.0	19	9.0
8	0.0	20	9.0
9	0.0	21	9.0
10	9.0	22	9.0
11	9.0	23	9.0

Hourly Status of Generators Open in Zip Code 92123

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	0.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	0.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92127

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	0.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	4.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	0.0	22	1.0
11	0.0	23	1.0

Hourly Status of Generators Open in Zip Code 92124

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	1.0	14	1.0
3	1.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	1.0	22	1.0
11	1.0	23	1.0

Hourly Status of Generators Open in Zip Code 92128

Hour	Open G.	Hour	Open G.
0	3.0	12	3.0
1	3.0	13	3.0
2	3.0	14	3.0
3	0.0	15	3.0
4	0.0	16	3.0
5	0.0	17	3.0
6	0.0	18	3.0
7	0.0	19	3.0
8	0.0	20	3.0
9	3.0	21	3.0
10	3.0	22	3.0
11	3.0	23	3.0

Hourly Status of Generators Open in Zip Code 92126

Hour	Open G.	Hour	Open G.
0	2.0	12	2.0
1	0.0	13	3.0
2	0.0	14	3.0
3	0.0	15	3.0
4	0.0	16	3.0
5	0.0	17	3.0
6	0.0	18	3.0
7	0.0	19	3.0
8	0.0	20	3.0
9	0.0	21	3.0
10	0.0	22	3.0
11	1.0	23	3.0

Hourly Status of Generators Open in Zip Code 92129

Hour	Open G.	Hour	Open G.
0	4.0	12	4.0
1	4.0	13	4.0
2	4.0	14	4.0
3	1.0	15	4.0
4	0.0	16	4.0
5	0.0	17	4.0
6	0.0	18	4.0
7	0.0	19	4.0
8	0.0	20	4.0
9	3.0	21	4.0
10	4.0	22	4.0
11	4.0	23	4.0

Hourly Status of Generators Open in Zip Code 92130

Hour	Open G.	Hour	Open G.
0	0	12	0
1	0	13	0
2	0	14	0
3	0	15	0
4	0	16	0
5	0	17	0
6	0	18	0
7	0	19	0
8	0	20	0
9	0	21	0
10	0	22	0
11	0	23	0

Hourly Status of Generators Open in Zip Code 92014

Hour	Open G.	Hour	Open G.
0	1.0	12	1.0
1	1.0	13	1.0
2	0.0	14	1.0
3	0.0	15	1.0
4	0.0	16	1.0
5	0.0	17	1.0
6	0.0	18	1.0
7	0.0	19	1.0
8	0.0	20	1.0
9	0.0	21	1.0
10	0.0	22	1.0
11	0.0	23	1.0

Hourly Status of Generators Open in Zip Code 92131

Hour	Open G.	Hour	Open G.
0	15.0	12	15.0
1	15.0	13	15.0
2	15.0	14	15.0
3	1.0	15	15.0
4	0.0	16	15.0
5	0.0	17	15.0
6	0.0	18	15.0
7	0.0	19	15.0
8	0.0	20	15.0
9	14.0	21	15.0
10	15.0	22	15.0
11	15.0	23	15.0

Hourly Status of Generators Open in Zip Code 92154

Hour	Open G.	Hour	Open G.
0	0	12	0
1	0	13	0
2	0	14	0
3	0	15	0
4	0	16	0
5	0	17	0
6	0	18	0
7	0	19	0
8	0	20	0
9	0	21	0
10	0	22	0
11	0	23	0

Hourly Status of Generators Open in Zip Code 92139