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Optimizing Power Line Undergrounding Decisions under Varying Wildfire Risk and Weather Scenarios

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***Abstract*—The threat of wildfire ignitions from electric power equipment has led utilities to increasingly turn to preemptive power shutoffs, which, while effective in reducing grid-induced wildfire risk, can cause significant load loss. Undergrounding power lines is an alternative strategy for preventing grid-induced wildfires. However, undergrounding lines is costly, so an efficient undergrounding plan must balance reductions in wildfire risk and load loss with the cost of undergrounding lines. We propose a robust optimization model to identify which power lines to underground to maximize load served while limiting wildfire risk across a range of wildfire risk and weather scenarios. Since solving this problem may be computationally heavy for large power grids and many operating scenarios, we present a delayed constraint generation algorithm to iteratively add scenarios until an optimal solution is found. We evaluate the performance of this framework on the RTS-GMLC with scenarios representing a year of operating conditions and compare it with a stochastic programming formulation. Our results indicate that our undergrounding model is successful in reducing load shed and risk compared to baseline cases in which no mitigation action is taken and only power shutoffs are implemented (no undergrounding). The robust formulation also reduces more load shed than the stochastic formulation in the most extreme scenarios.**

***Index Terms*—grid resilience, optimization, transmission systems, underground power lines, wildfire risk.**

I. Introduction

Climate change impacts power system planning and operations both through increased variability in generation from renewable resources and outages caused by extreme weather events. Wildfires, in particular, have become more frequent and severe in recent years in the western U.S. and Canada [1] and high risk wildfire conditions are projected to increase globally [2]. Careful planning is necessary to design a power system that is resilient to an ever-changing climate. Here, we seek to improve grid resilience in the context of elevated wildfire risk and variable wind and solar generation and load.

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A. Wildfires and the Electric Grid

Power systems have a unique relationship with wildfires compared to other extreme events. Power equipment can be damaged by fires, but can also ignite wildfires via electrical fault currents [3]. To prevent the latter, utilities currently implement preemptive power shutoffs in which portions of the grid are de-energized to reduce the risk of electrical faults and potential ignitions [4]. However, while effective in reducing fire ignitions, power shutoffs may result in harmful customer outages [5]. To balance the competing objectives of wildfire risk reduction and satisfying electricity demand, researchers have proposed optimization models to select components to de-energize [6].

Long-term mitigation actions (on the scale of months to years) can reduce the risk of fire ignitions while limiting dependence on short-term mitigation actions. Options include vegetation and forest management [7], as well as electric infrastructure hardening, e.g., insulating conductors and installing fire-resistant poles. Converting overhead power lines to underground cables is a particularly effective measure since it eliminates the potential for wind-caused blowdown or conductor contact with vegetation or animals. Researchers have proposed optimization-based methods to determine how to implement long-term wildfire risk mitigation [8]–[10]. However, these works do not consider variability of both wildfire risk and other environmental conditions.

Modeling variability of wildfire risk and other environmental conditions is important to capture the diversity in future operating scenarios. Different times, days, seasons, and years can exhibit different geospatial distributions of wildfire risk, as well as other environmental conditions (e.g., wind, solar irradiance, temperature) that impact electricity supply and demand. In this paper, we focus on grid planning to minimize wildfire risk and load shed while also taking into account variability of wildfire risk and weather scenarios.

B. Planning with Robust Optimization

Power system planners must make decisions about the future electric grid without full knowledge of the environment that the grid will operate under. Stochastic optimization (SO) and robust optimization (RO) are widely used to make decisions under uncertainty and variability. While SO aims to minimize the expected cost across a set of scenarios, RO minimizes the worst-case cost across scenarios, possibly within some tolerance for how conservative the solution may be.

Wildfires are high-impact but low-frequency events. While many fires occur over time, the probability of a wildfire ignition at a particular time and location is vanishingly small. Wildfire risk also varies across seasons and years. Along with wildfire risk conditions, load and generation availability are also difficult to predict in the long-term due to variability over time and changing climate conditions. Furthermore, renewable resource availability, load, and wildfire risk are highly correlated. For example, fires are more likely to start under windy conditions, and high temperatures increase both fire risk and load. For this reason, it is important that operating scenarios represent all of these aspects simultaneously.

SO requires scenario probabilities as model inputs, but in the case of wildfires, the probability of each wildfire risk realization is difficult to assess and may be extremely small. Since SO models evaluate the expected impacts, where the impacts of individual scenarios are weighted with the respective probabilities, the solutions can be very sensitive to errors in the probabilities. In contrast, an RO model can consider wildfire risks that vary by scenario without making explicit assumptions on the exact probability of a particular wildfire occurring. Furthermore, by minimizing worst-case risk, RO limits impacts in the highest risk scenarios, spending less effort on evaluating and mitigating impacts in less severe scenarios.

We develop an RO model that determines power line undergrounding decisions to minimize the worst-case load shed across a set of scenarios representing variable wildfire risk, generation availability, and load. Our model adaptively selects the worst-case scenario depending on the undergrounding decisions made such that no other scenario can lead to higher load loss. We manage wildfire risk by forcing lines above a specified risk threshold to be shut off if not undergrounded, which reflects common industry practice [4]. To control for the conservativeness of the solution in planning for the worst case, we constrain the budget for undergrounding lines and vary this budget, along with wildfire risk tolerance, across model runs. Additionally, we compare our results to a stochastic variant of the model under the assumption that all scenarios are equally weighted (i.e., have the same probability of occurring), as data on the actual probabilities of these scenarios are not available.

Bayani and Manshadi [11] also propose a robust model for grid planning to balance wildfire risk mitigation and load shed. Like [9], their model includes a range of investment decisions, such as hardening transmission lines (e.g., undergrounding lines, managing vegetation, and replacing aging components) and installing new transmission lines, generation, and storage. In this paper, we choose to focus on line undergrounding, which aligns with recent focus from utilities on this mitigation strategy. For example, Pacific Gas & Electric (PG&E) plans to underground an estimated 2,300 miles of transmission lines by 2026, with a goal of eventually increasing the total to 10,000 miles to reduce wildfire risk [12]. The reduced complexity of our model allows us to plan hardening for larger cases than seen in the previous studies. Here, we determine undergrounding plans for a moderately-sized test system (73 buses) with a full year of real-world wildfire risk scenarios.

C. Contributions

Our contributions are twofold: a modeling framework and solution algorithm. We develop a novel robust optimization model for line undergrounding to minimize load shed across a set of scenarios representing wildfire risk, generation availability, and load (Sec. II). Since this mixed-integer program may be computationally intensive to solve across a large number of scenarios, we also develop a delayed constraint generation algorithm to iteratively add scenarios until an optimal solution is found (Sec. III). This algorithm is trivially parallelizable across scenarios, fostering the solution of problems with a very large number of scenarios. We demonstrate the use of our proposed model on the Reliability Test System from the Grid Modernization Lab Consortium (RTS-GMLC) and assign wildfire risk values based on the Wildland Fire Potential Index (WFPI) maps [13], as described in Sections IV and V.

Our planning model provides a tool to help power system planners design resilient future electric grids in the complex context of wildfires and their relationship to other grid-impacting weather factors.

II. Problem Formulation

We develop a robust optimization model to minimize the worst-case load shed across a set of scenarios. Although the robust optimization model is the focus of this paper, we also present a stochastic variant of the model for comparison.

A. Robust Optimization Model

We seek to minimize the worst-case load shed across all scenarios, where a scenario is defined by the wind and solar power potential, load, and wildfire risk corresponding to the environmental conditions at a specific point in time.

1) Operational rules to reduce wildfire risk: It is common practice for utilities and researchers to quantify branch-wise wildfire risk values that represent the risk associated with a wildfire ignition caused by that specific branch. Large utilities have sophisticated processes for assessing risk from various (potentially private) sources [4]. In this paper, we determine this risk based on publicly available wildfire potential maps [13] (as done in [8]), which quantify the potential for fire spread due to natural factors. Additional impacts, such as the threat of a fire to people and structures, are also important aspects of ignition risk, but quantifying these impacts requires significant data processing efforts and thus is reserved for future work.

For each instance of the model that is run, we set a wildfire risk threshold. Branches with risk above this threshold (i.e., "risky lines") for a given scenario will be available if and only if they are undergrounded. Branches below the wildfire risk threshold will be available regardless of undergrounding status. For scenario, s, we call the set of branches that are above this threshold, $\mathcal{L}_s^{\text{risky}}$.

2) Optimization formulation: We can model this problem as the following tri-level optimization problem,

$$\min_{\boldsymbol{z}} \max_{\boldsymbol{x}} \min_{\boldsymbol{\theta},\boldsymbol{p}} \sum_{s\in\mathcal{S}} \sum_{b\in\mathcal{B}} p^{\text{shed}}_{b,s} x_s \tag{1a}$$

$$\text{s.t.} \sum_{s\in\mathcal{S}} x_s = 1 \tag{1b}$$

$$\sum_{l\in\mathcal{L}} c_l z_l \leq C^{\mathcal{U}} \tag{1c}$$

$$\sum_{\ell\in\delta^-(b)} p^{\mathcal{L}}_{l,s} + \sum_{g\in\mathcal{G}_b} p^{\mathcal{G}}_{g,s} = \sum_{\ell\in\delta^+(b)} p^{\mathcal{L}}_{l,s} + D_{b,s} - p^{\text{shed}}_{b,s} \quad \forall\, b\in\mathcal{B}, s\in\mathcal{S} \tag{1d}$$

$$p^{\mathcal{L}}_{l,s} = b_l(\theta_{o(l),s} - \theta_{d(l),s}) \quad \forall\, s\in\mathcal{S}, l\in\mathcal{L}\backslash\mathcal{L}^{risky}_s \tag{1e}$$

$$b_l(\theta_{o(l),s} - \theta_{d(l),s}) - M(1-z_l) \leq p^{\mathcal{L}}_{l,s} \leq b_l(\theta_{o(l),s} - \theta_{d(l),s}) + M(1-z_l) \quad \forall\, s\in\mathcal{S}, l\in\mathcal{L}^{risky}_s \tag{1f}$$

$$-\overline{P}^{\mathcal{L}}_l \leq p^{\mathcal{L}}_{l,s} \leq \overline{P}^{\mathcal{L}}_l \quad \forall\, s\in\mathcal{S}, l\in\mathcal{L}\backslash\mathcal{L}^{risky}_s \tag{1g}$$

$$-\overline{P}^{\mathcal{L}}_l z_l \leq p^{\mathcal{L}}_{l,s} \leq \overline{P}^{\mathcal{L}}_l z_l \quad \forall\, s\in\mathcal{S}, l\in\mathcal{L}^{risky}_s \tag{1h}$$

$$0 \leq p^{\mathcal{G}}_{g,s} \leq \overline{P}^{\mathcal{G}}_{g,s}, \quad \forall\, s\in\mathcal{S}, g\in\mathcal{G} \tag{1i}$$

$$0 \leq p^{\text{shed}}_{b,s} \leq D_{b,s}, \quad \forall\, s\in\mathcal{S}, d\in\mathcal{D} \tag{1j}$$

$$z_l \in \{0,1\} \quad \forall l\in\mathcal{L} \tag{1k}$$

$$x_s \in \{0,1\} \quad \forall s\in\mathcal{S}, \tag{1l}$$

where the objective (1a) minimizes system-wide load shed in the worst-case scenario. The three problems are described below.

In the outermost problem, the power system planner decides which lines to underground, represented by the binary variable $\boldsymbol{z}$, where z_l is 1 if line l is undergrounded, 0 otherwise (Constraint (1k)). Line l costs c_l to underground, and the total budget for undergrounding lines is given by $C^{\mathcal{U}}$. Constraint (1c) limits the total undergrounding cost to be within this budget.

In the middle problem, the worst-case scenario, that is, the scenario maximizing load shed for a given set of undergrounding decisions, is selected. The binary variable x_s is 1 if scenario s is selected, 0 otherwise (Constraint (1l)). We allow at most one scenario to be selected in Constraint (1b).

The innermost problem determines how to operate the grid to minimize load shed across buses for the worst-case scenario. The variable $p^{\text{shed}}_{b,s}$ is the load shed at bus b for scenario s. Constraints (1d – 1j) form a DC approximation of the power flow equations. Constraint (1d) requires that flow into a bus must equal flow out, where $p^{\mathcal{L}}_{l,s}$ is the flow on branch l in scenario s, $p^{\mathcal{G}}_{g,s}$ is the generation at generator g in scenario s, and $D_{b,s}$ is the load at bus b in scenario s. The sets $\delta^-_{(b)}$ and $\delta^+_{(b)}$ represent branches terminating and originating at bus b, respectively, while $\mathcal{G}_b$ is the set of generators located at bus b. Constraints (1e) represent the power flow on the set of non-risky lines $\mathcal{L}\backslash\mathcal{L}^{risky}_s$ (i.e., lines that would not have to be de-energized if not undergrounded in scenario s) where $\boldsymbol{\theta}$ are the voltage angles and $o(l)$ and $d(l)$ represent the origin and destination bus of branch l, respectively. Constraints (1f) represent the power flow on the set of risky lines $\mathcal{L}^{risky}_s$ (i.e., lines that have to be de-energized if they are not undergrounded). These constraints ensure that the normal power flow constraints are enforced if the line is undergrounded ($z_l = 1$), while removing any restrictions on the angle difference if the line is de-energized. We use a big-M formulation for these constraints, which allow the voltage angle differences across de-energized lines to be between $-M$ and M.[1] Thus, constraint (1f) will be inactive for lines that are above the risk threshold ($l \in \mathcal{L}^{risky}_s$) but not undergrounded ($z_l = 0$). Similarly, constraints (1g) and (1h) limit power flows based on line thermal capacity for lines that are below the risk threshold and risky lines that are undergrounded. The flow on risky lines that are not undergrounded is forced to 0 because these lines will be de-energized. Power production is limited by the available power $\overline{P}^{\mathcal{G}}_{g,s}$ at each generator in the specific scenario (Constraint (1i)). In our current tests, this parameter is varied by scenario for wind and solar generators, but fixed to the generator capacity for other generator types. However, it could vary by scenario for other generator types as well, given different input data. Load also varies by scenario and load shed at each bus is restricted to be no more than the demand for the given scenario as implied by Constraint (1j).

By enforcing the optimal power flow (OPF) constraints across all scenarios and adaptively selecting the worst-case scenario relative to the undergrounding decisions, we know that no other scenario could cause greater load shed than the worst-case scenario selected.

We can convert this tri-level optimization model into the following equivalent[2] single-level optimization model by adding an auxiliary variable, p^{shed}, representing the total load shed in the worst-case scenario,

$$\min_{\boldsymbol{z},\boldsymbol{\theta},\boldsymbol{p}} \quad p^{\text{shed}} \tag{2a}$$

$$p^{\text{shed}} \geq \sum_{b\in\mathcal{B}} p^{\text{shed}}_{b,s} \quad \forall\, s\in\mathcal{S} \tag{2b}$$

$$(1c) - (1k) \tag{2c}$$

The objective (2a) minimizes the worst-case total load shed, which must be greater than or equal to the total load shed in any scenario (Constraint (2b)). Constraint (2c) enforces the undergrounding budget and DC power flow equations with the fire mitigation policy.

B. Stochastic Optimization Model

We also implement an SO variant of problem (1) for comparison purposes. Problem (1) can be converted to the

[1]We use a big M value equal to the branch susceptance $|b_l|$ multiplied by the sum of the N greatest voltage angle difference limits, where N is the number of buses in the network. This value is large enough to not overly restrict bus voltage angles across inactive lines, but is not too large to cause numerical issues for our test cases.

[2]Note that Problem (2) does not directly give optimal values for the decision variables $\boldsymbol{x}$, but these could be derived by comparing the load shed in each scenario to the maximum load shed, p^{shed}.

following stochastic program,

$$\min_{\boldsymbol{z},\boldsymbol{\theta},\boldsymbol{p}} \quad \sum_{s\in\mathcal{S}}\sum_{b\in\mathcal{B}} \omega_s p^{\text{shed}}_{b,s} \tag{3a}$$

$$(1c) - (1k), \tag{3b}$$

by removing the variable $\boldsymbol{x}$ and instead minimizing the expected load shed across scenarios (Constraint (3a)), where ω_s is the probability of scenario s occurring. We assume $\omega_s = \frac{1}{|\mathcal{S}|}$ for all scenarios, since the actual probabilities of wildfire scenarios occurring are unknown and likely very small. Again, Constraint (3b) enforces the budget, DC power flow, and risk policy constraints. As a note, the SO problem, as it is formulated here, can not be directly used with Algorithm 1 (described below).

III. Solution Method

For relatively small systems and a small number of scenarios, Problem (1) can be solved directly using commercial optimization solvers. However, the complexity of the problem grows with the number of lines, which can be in the tens or hundreds of thousands for realistically sized power grids (e.g., the California Test System (CATS) [14]). Additionally, adequately representing the range of uncertainty in future climate may require a large number of scenarios, which would greatly increase the size of the constraint set (1d) – (1j). We develop a delayed constraint generation algorithm that optimizes initially over a subset of scenarios and adds scenarios iteratively until an optimal solution is found. We compare the runtime of this algorithm to solving Problem (2) directly for the computational test case.

Notice that for a given undergrounding solution, $\boldsymbol{z}$, Constraints (1d) – (1j) can be decomposed by scenario. More specifically, for a given undergrounding solution, $\boldsymbol{z}$, and scenario, s, we can find the minimum load shed by solving the following problem,

$$p^{\text{shed}*}(\boldsymbol{z}, s) = \min_{\boldsymbol{\theta},\boldsymbol{p}} \quad \sum_{b\in\mathcal{B}} p^{\text{shed}}_{b,s} \tag{4a}$$

$$(1c) - (1j) \text{ for } \mathcal{S} = s \tag{4b}$$

Let $\mathcal{S}^{\text{wc}}$ be the set of possible worst-case scenarios identified so far. Starting from one scenario, we iteratively solve Problem (2) for this subset of scenarios, and add scenarios with higher load shed in Problem (4) to $\mathcal{S}^{\text{wc}}$ until no scenario causing greater load shed than any scenario in $\mathcal{S}^{\text{wc}}$ can be found. This algorithm is outlined in Alg. 1.

For the initialization of $\mathcal{S}^{\text{wc}}$ in Step 1, we choose a random scenario. Other options are to choose the scenario with the highest initial load shed or the most lines above the specified risk threshold. The choice of heuristic may impact the number of iterations and runtime and therefore will be an important focus of future work that considers larger test cases.

IV. Test Case Setup

We evaluate model performance using the RTS-GMLC case, a synthetic transmission grid model with time-varying renewable generation and load profiles, geo-located in the southwest U.S. [15]. Case parameters, including nominal values for demand and generation capacity, are given in Table I. Time-series data for solar, wind, and load are available in the RTS-GMLC GitHub repository [15] for 2020. To quantify the maximum generator capacities $\overline{P}^{\mathcal{G}}_{g,s}$ for solar and wind generators, we use the MW value given in the RTS-GMLC data for the corresponding generator and date. The load time-series data for RTS-GMLC are provided as aggregate values for three regions of the test case. We first compute each load's share of total nominal demand, then disaggregate the regional time-series values based on those proportions to assign demand $D_{b,s}$ to each load bus and scenario.

Algorithm 1:

Input: Complete set of scenarios, $\mathcal{S}^{\text{all}}$.

1 Initialize $\mathcal{S}^{\text{wc}} = \{s^{\text{rand}}\}$

2 Solve Problem (2) for $\mathcal{S} = \mathcal{S}^{\text{wc}} \rightarrow p^{\text{shed}*}, \boldsymbol{z}^*$;

3 **if** $\max_{s\in\mathcal{S}^{all}\setminus\mathcal{S}^{wc}} p^{shed*}(\boldsymbol{z}^*, s) > p^{shed*}$ **then**

4     $\mathcal{S}^{\text{wc}} = \mathcal{S}^{\text{wc}} \cup \{s \in \mathcal{S}^{\text{all}}\setminus\mathcal{S}^{\text{wc}} : p^{\text{shed}*}(\boldsymbol{z}^*, s) > p^{\text{shed}*}\}$
    Go to step 2 ;

5 **end if**

6 **return** $\boldsymbol{z}^*$ optimal undergrounding decisions

TABLE I
Parameters for RTS-GMLC computational study.

Component	Quantity
Buses	73
Power lines	120
Generators	158
Loads	51
Demand	8,550 MW
Generation capacity	14,550 MW
Solar generation capacity	2,916 MW
Wind generation capacity	2,508 MW
Line undergrounding cost	\$2 mil/mi
Line undergrounding budget	4% of total
Line risk threshold	120
Number of scenarios	360

To quantify the wildfire risk of each power line in the RTS-GMLC, we leverage the WFPI [13]. The WFPI is a unitless measure of vegetation flammability; large fires and fire spread tend to occur at higher WFPI indices. The WFPI maps are published once daily, and we utilize daily maps for the year 2021. For this paper, we assign the maximum intersecting WFPI value to be the singular risk value for the entire power line. Other methods for assigning risk values to power lines are discussed in previous work [8], [16]. We define the set of risky lines $\mathcal{L}^{risky}_s$ for each scenario as all lines with risk values above 120. We use 2 million USD per mile of line length as the cost to underground lines, as reported by PG&E [17]. We vary the undergrounding budget, $C^{\mathcal{U}}$, as a percent of the cost to underground all lines, choosing 4% as the baseline.

We create a scenario set by sampling the RTS-GMLC time-series data to obtain a single timestep for each day (at noon), so that we have a total of 360 scenarios.[3] Each scenario represents weather conditions at a single timestep and is defined by a set of parameters: available generation capacity for renewable generators, demand for all buses, and risk values for all lines.

All test cases are implemented in Python using the Pyomo algebraic modeling language [18] and solved using Gurobi on a personal computer.

V. Results

A. Illustrative Example and Benchmarking

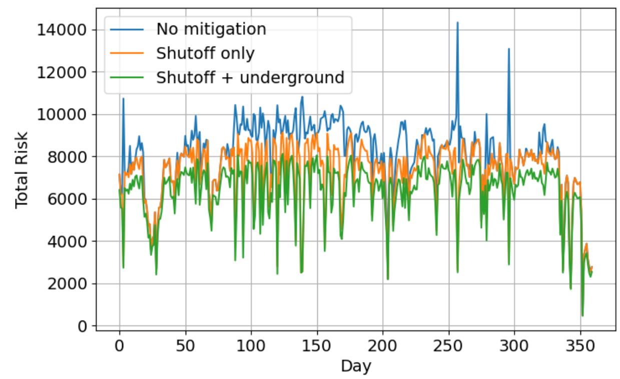
Given the model setup above, the investment problem chooses to underground 10 out of 120 lines. To evaluate the performance of this investment plan, we solve the scenario-specific problems in Eq. (4) for three different cases: *no mitigation* (i.e., we do not de-energize any lines, which can mathematically be represented by setting all z_l variables equal to 1), *shutoffs only* (i.e. we assume that all risky lines have to be de-energized, which can mathematically be represented by setting all $z_l \in \mathcal{L}_s^{risky}$ equal to 0), and *shutoffs and undergrounding* (i.e., our proposed model). For each scenario, we record the total load shed and total wildfire risk associated with the energized lines.

Fig. 1(a) shows the per-scenario sum of wildfire risk across all energized power lines. The *no mitigation* case (blue), represents the baseline system risk that is present when no risk management strategy is implemented.[4] The *shutoffs only* case (orange) shows how line de-energization is able to reduce the overall risk, especially for scenarios with high baseline risk. The *shutoffs and undergrounding* case (green) exhibits even lower risk. Note that increasing the undergrounding budget would push the *shutoffs and undergrounding* risk even lower. If we were to decrease the line risk threshold, then both the *shutoffs only* and *shutoffs and undergrounding* results would shift lower.

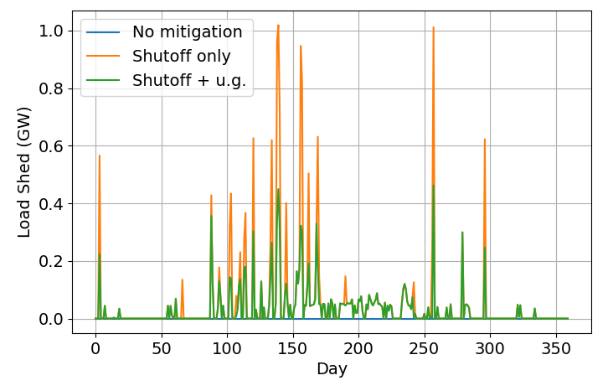
Fig. 1(b) shows the load shed obtained from the operations problem for the three mitigation cases. Note that there is no load shed for any scenario in the *no mitigation* case since only load shed from planned line de-energizations was included. However, a grid without planned mitigations would be more susceptable to forced outages due to wildfires. For the *shutoffs only* and *shutoffs and undergrounding* cases, there are several scenarios with high load shed due to line shutoffs; each of these peaks is lower in the case with undergrounding. If we increase the budget for undergrounding, the load shed peaks for the *shutoffs and undergrounding* case would be further reduced. Conversely, if we reduced the risk threshold, we would expect the load shed in both cases to increase.

[3] We use daily scenarios rather than hourly because the WFPI is published once per day. The WFPI data is missing 5 dates, so we have 360 scenarios, not 365.

[4] The elevated risk outside of southern California's typical wildfire season (May-October) may be a result of assigning the maximum intersecting WFPI value to each line. See [16] for a comparison of different risk aggregation methods.



(a) Wildfire risk (total across all lines)



(b) Load shed (total across all buses)

Fig. 1. RTS-GMLC operation under 3 wildfire mitigation cases: no mitigation (blue), shutoffs only (orange), and shutoffs and undergrounding (green). Note that each scenario corresponds to a day of the year.

B. Computational Efficiency of RO Solution Methods

As discussed in Sec. III, it is possible to either solve Prob. 1 directly or use Alg. 1 to determine the optimal undergrounding plan. Here, we compare the runtime for these two methods. We initialize $\mathcal{S}^{wc}$ with the first scenario in our set (Jan. 1, 2020). We verify that we obtain the same objective value for both solution methods, which is a worst-case load shed of 175.5 MW corresponding to the July 27th scenario, and the same set of 10 lines selected for undergrounding.

Solving Prob. 1 directly takes 179.0 seconds. Solving Alg. 1 takes 12 iterations and 564.7 seconds. For this moderately-sized test case, solving the algorithm is not faster than solving the full problem with all scenarios. However, this is not entirely unexpected for a small test case. We expect that, for realistically-sized power grids solved across a large set of scenarios, the problem size would grow large enough to warrant starting with a subset of scenarios and generating constraints for additional scenarios as needed, as in Alg. 1. Note that Alg. 1 is also trivially parallelizable, a feature we did not take advantage of in our initial implementation. Parallelizing the algorithm would enable us to solve the problem more quickly across a larger number of scenarios.

Preliminary findings on larger test cases indicate that solving the algorithm is faster than solving the extensive form.

C. Robust Versus Stochastic Solutions

Next, we compare solutions for the robust (Prob. 1) and stochastic (Prob. 3) model formulations. The optimal objective values found for the baseline are 175.5 MW and 461.9 MW for the SO and RO problems, respectively. Note that these objectives cannot be directly compared since the SO problem minimizes the expected load shed whereas the RO problem minimizes the worst case load shed. The 9 lines selected for undergrounding for the SO problem are slightly different from the 10 selected for the RO problem, as depicted in Fig. 2; there are 5 lines in common. Note that some of the lines selected are very short connecting lines. Generally, the lines selected are in the top right area, with the exception of two lines in the left-most area of the grid – one selected by SO only and one selected by both RO and SO. These preliminary results demonstrate that the robust and stochastic approaches to addressing weather variability lead to different locations for optimal undergrounding decisions.

To further compare the RO and SO solutions, we examine the wildfire risk and load shed that result from the operations of each. For this comparison, we run the load shed minimization, Prob. 4, with undergrounding decisions z obtained from the RO and SO solutions for each of the 360 scenarios. As the risk threshold is the same between these two cases, the realized per-scenario wildfire risk is very similar for both methods. The load shed over time is shown in Fig. 3. We first observe that the RO undergrounding solution leads to a non-zero load shed on 134 days of the year, whereas SO solution only has 73 days with non-zero load shed. We also compute the worst-case (maximum) and average load shed across all scenarios in the operational results of the RO and SO undergrounding plans (Fig. 3). The maximum operational load shed from the SO plan is 509.2 MW, which is 10.2% higher than the maximum load shed from the RO plan of 461.9 MW. The average load shed from the SO plan of 17.6 MW, however, is 43.8% lower than that of the RO plan at 31.3 MW.

We plot load shed peaks above 0.2 GW, which correspond to the 13 most extreme scenarios, in Fig. 4. Of these cases, the SO undergrounding plan produces more load shed in 9 scenarios (including the three highest load shed peaks) compared to 4 in the robust plan. While the SO plan produces the maximum load shed, the SO plan still has a slightly lower (yet similar) average load shed (318.1 MW) than the RO plan (323.9 MW) for this set of extreme scenarios.

These results demonstrate that the robust undergrounding plan is successful in managing load shed in extreme scenarios. However, we also see that the RO plan may produce slightly more load shed on less-extreme days. I.e., the RO solution thus is able to reduce worst-case load shed at the expense of more frequent shutoffs and higher average load shed. The 'better' solution is thus a matter of interpretation; the RO problem may avoid very large outages, while the SO problem may reduce the frequency and scale of moderately-sized ones.

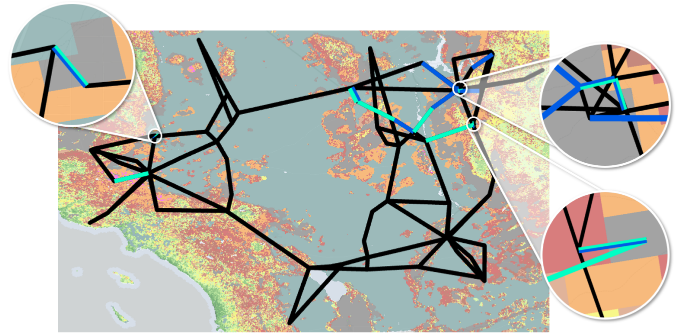


Fig. 2. Lines undergrounded in the robust (dark blue) and stochastic (turquoise) problems, overlaid on the Wildland Fire Potential Index map for July 27, 2021.

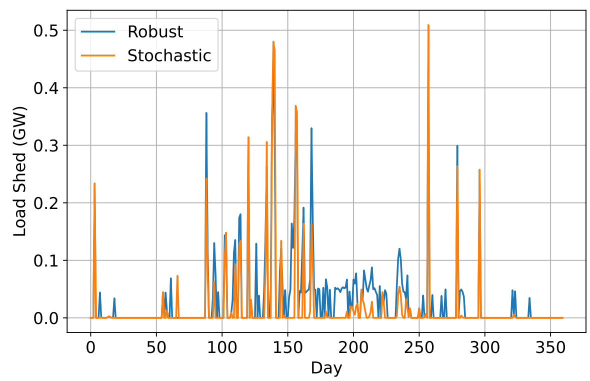


Fig. 3. Load shed for the robust and stochastic undergrounding plans.

D. Sensitivity to Model Parameters

In the previous test cases, we selected the risk threshold and undergrounding budget without justification. A grid planner may want to conduct a sensitivity analysis on these parameters to determine appropriate choices that will result in an acceptable level of load shed. In Fig. 5, we show how the worst-case load shed obtained from solving the RO problem varies as a function of both the budget and risk threshold.

We can see from this example that large budgets do not result in more favorable worst-case load shed and therefore it would not make sense for a planner to choose a higher

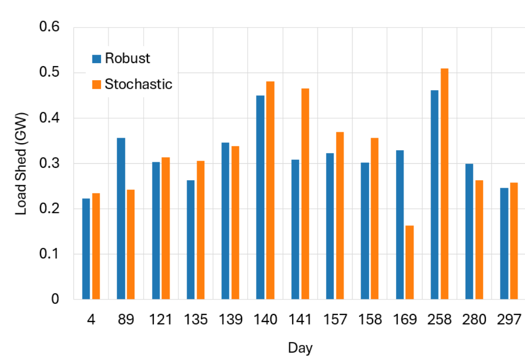


Fig. 4. Load shed for the highest-cost scenarios (above 0.2 GW) from the robust and stochastic undergrounding plans.

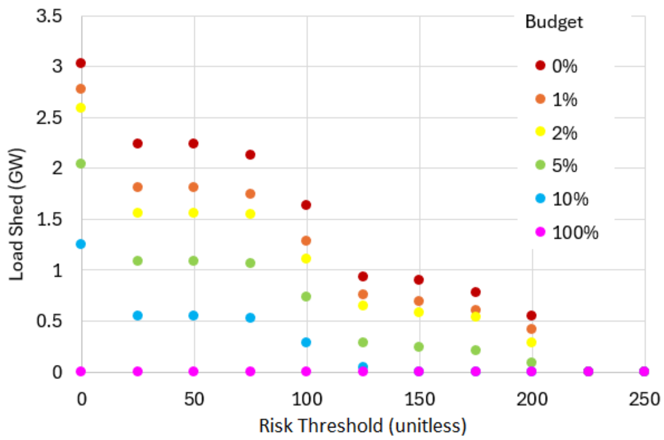


Fig. 5. Plot of the total load shed (GW) as a function of the wildfire risk threshold. Each series corresponds to a different investment budget, shown as a percent of the total cost to underground all lines.

budget. For lower budgets, we see that higher risk thresholds result in a more favorable worst case load shed. A higher risk threshold means that we are less conservative in our line de-energization policy. Thus, it is also in a planner's best interest to examine the solutions' accepted wildfire risk when choosing an appropriate threshold of which lines are considered "risky".

VI. Conclusion

This paper presents a robust optimization (RO) framework for planning electric power line undergrounding to mitigate wildfire risk while minimizing load shed. Due to the variability of environmental conditions and the low probability of wildfire ignitions from power equipment, it is challenging to determine which infrastructure upgrades will lead to the most favorable grid operations outcomes. Our modeling approach represents wildfire risk, solar and wind generation availability, and electricity demand as a discrete set of operating scenarios and selects an undergrounding plan that minimizes load shed to customers in the worst case.

We demonstrate the use of our optimization model and solution algorithm using the 73-bus RTS-GMLC and publicly available wildfire risk maps. We compare the load shed and risk when risky lines are undergounded or de-energized to when risky lines are only de-energized and to when no risk mitigation is taken. We also compare the solution of the RO problem with a SO problem and find that the RO model reduces load shed more than SO in extreme cases but less on average. However, RO has the added benefit that it eliminates the necessity to assume wildfire scenario probabilities, which are each very low and difficult to assess.

While we observe that our optimization problem can be solved directly using commercial solvers for RTS-GMLC, we expect that larger test cases will carry a significant computational burden. Thus, a constraint generation approach is proposed for the case in which solving the problem directly is too computationally challenging. In future work, we plan to test our model on a larger, more realistic synthetic test case, such as CATS [14], with correlated fire risk, solar and wind capacity, and demand data produced from the same weather inputs. We would also like to consider multi-period storage decisions and load loss over time, which would also make the problem more difficult to solve directly, in future work.

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