Electric power network charger placement for extreme event resilience via submodular optimization

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ABSTRACT

Efficient evacuation procedures in urban environments are crucial for ensuring public safety. We study the problem of optimizing the placement of "smart chargers" for electric vehicles to maximize the expected ability for successful evacuation in the event of an emergency. The proposed solution to this problem is based on a submodular optimization framework to determine the optimal set of locations for placing the chargers. The method takes into account factors such as the distribution of at-risk populations, and the availability of evacuation routes. By modeling these factors and the placement of chargers as submodular functions, we efficiently search for the optimal placement of the chargers while ensuring that the solution is economically viable via cardinality constraints. Simulations on physically realistic electric power network models—combined with real-world extreme event datasets—are used to verify the results. The proposed method can have important implications for policymakers and engineers who are responsible for ensuring the resiliency of electric power networks during extreme events.

CCS CONCEPTS

• **Hardware** → **Power networks**; **Power estimation and optimization**.

KEYWORDS

decision-making under uncertainty, transporation networks, electric power networks, smart chargers

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Availability of Data and Material:
The **webpage** for the data and code used in this paper is available at https://github.com/samtalki/NetworkPlacement.jl

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1 INTRODUCTION AND MOTIVATION

We study the problem of bolstering the resilience of electrified transportation networks under the uncertainty of extreme events. In particular, the goal of the proposed research is to solve the problem of *optimizing the placement* of electric vehicle smart chargers within an electric power distribution network, such that the amount of serviced customers during extreme events will be maximized.

Summarily, the completed solution to this problem at the end of the semester will be composed of an efficient integer programming algorithm to place electric power network chargers in pursuit of this goal. The proposed method will be a valuable policy-making and engineering tool to ensure public safety in urban environments during extreme events. The proposed method, which is illustrated conceptually in Fig. 1, will comprise several key properties, which we summarize below.

(1) Mathematically rigorous—the proposed method will be based on the well-studied and popular "submodular" optimization technique, which allows for set-theoretic decision variables.
(2) Physically valid—physics-informed constraints for feasible operation of an electric power network will be integral to the method, and fundamental to the algorithm.
(3) Socially conscious—the algorithm will consider socioeconomic factors to ensure scalable and equally-spread chance of evacuation in an extreme event. Regularization to ensure the spread of chargers given distributions of at-risk populations will be considered.

This proposal outlines the engineering problem, the proposed solution to this engineering problem, related work, and project accomplishments.

The goal of the proposed optimization problem will be to minimize the *expected network vulnerability* of the electric power network such that probability of evacuation in an extreme event is maximized.

2 SURVEY OF RELATED WORK

2.1 Evacuation studies using electric vehicles

There have been two main studies in the past regarding evacuation from natural disasters using electric vehicles. One of the studies [1] examines the power demand during the evacuation before Hurricane Irma event to investigate the challenge of commonly using electric vehicles for hurricane evacuation. The results of [1] suggest that Florida would face serious challenge in power supply if the majority of evacuating vehicles are electric vehicles. The main strength of [1] is that several edge cases and situations are considered when describing the specific Florida case study. For instance,

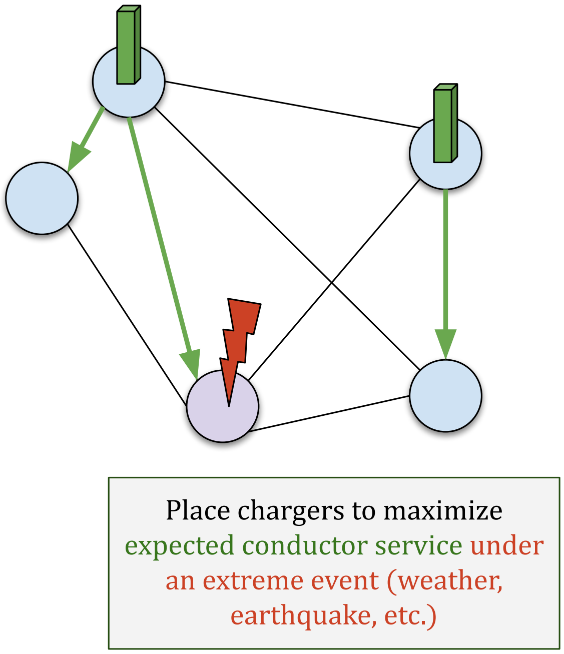

Figure 1: Illustration of the proposed problem and solution: optimal placement of electric vehicle chargers in an electric power network for resilience to an extreme weather event.

the paper highlights the potential risk of not accounting for extreme failure of the power network in the analysis. To cover this edge case, the paper recommends to consider the EV adoption level based on power system's capacity. Another strength of the paper is it provides policymakers with potential solutions on how to address the main issue of evacuating from hurricanes using EVs. Two of the solutions include developing centralized charging strategies and improving battery technology. One weakness of this paper is it only considers one natural disaster. The study is purely focused on the possibilities of evacuating from a hurricane event using electric vehicles. This weakness can be addressed by focusing on evacuating using EVs from natural disasters in general, not just hurricanes. Additionally, the paper does not provide any type of evacuation planning during the disaster event. It just answers the question of whether evacuation will be possible from a hurricane event using EVs.

A second study, [2], addresses the main weaknesses of the first paper by providing a three-stage method for optimal mass evacuation planning for electric vehicles before natural disasters. The input to this problem includes a network and a set of evacuation demands. The output is the evacuation plan (which includes routes and departure schedule). The first stage excludes long evacuation paths out of consideration using a specialized shortest path algorithm. The second stage reassigns greater amount of charging stations for locations with greater electric vehicle traffic in order to balance charging demands. The third stage solves a set of candidate paths for each origin-destination EV flow. It also formulates an evacuation planning model which includes routes and department schedule. A case study of Florida hurricane evacuation is also conducted to measure the method's effectiveness. The main strength of this paper is it provides evacuation planning. It is essential since by providing this sort of planning, the paper not only clarifies the possibility of successful evacuation from natural disasters using EVs but also a detailed planning on how the evacuation can be carried out. Another strength of this paper is the proposed three-stage method is evaluated using a Florida based case study. This is useful since it helps understand the effectiveness of the method in real-world scenarios. One of the main weakness of the paper is that it assumes the charging station availability is knowing during the planning stage. However, this is not usually the case during real situations. This weakness can be addressed by exploring a more robust model that considers the possibility of disruptions such as electricity failure. Additionally, these two papers interrelate as both attempt to answer whether mass evacuation from natural disasters using EVs is possible. However, they differ in the way they answer this question. The first paper only comments on the possibility of mass evecuation using EVs. The second paper not only clarifies the possibility of successful evacuation from natural disasters using EVs but also provides a detailed planning on how the evacuation can be done.

2.2 Charger placement techniques

The placement of chargers for electric vehicles is also a widely studied problem. The EV charging station placement problem has been shown to be non-polynomial time hard [3], yet there have been attempts to find heuristic solutions. Lam et al. [4] modeled this as a mixed integer programming problem to optimize location placements in Seattle Downtown. It minimizes access costs while penalizing on unmet demand. The model is generalizable to other city centers. This can work great if the power load is geographically balanced, but EVs are mobile and in the case of a disaster their movement can create unanticipated increases in demand at various locations in the grid along evacuation routes. Daniel et al. [5] studies the resiliency of power systems in the event of a wildfire in a world where EVs are very prevalent. They combine Resiliency Analysis and probabilistic models of load distribution while factoring in evacuation routes and claim to have found a more realistic resiliency estimate in such a setting.

While looking into the topic of evacuation planning for electric vehicles prior to natural disaster events and placement of chargers for electric vehicles, it is also important to consider fairness. Essentially, it is critical to ensure everyone has fair access to charging stations without any unfair advantage towards certain entities. A study [6] proposes a recommendation system (FairCharge) to minimize the total charging idle time while considering the fairness constraints. The main strength of this study is that idle time for charging is minimized without constructing additional charging infrastructures. This is great because constructing additional infrastructure will increase costs and efforts. Another strength is that the paper evaluates FairCharge using a case study to show its effectiveness. Specifically, it is evaluated with real-world streaming data from Shenzhen, China. The results of the study indicate that this system reduces queuing time and idle time of Shenzhen electric taxi fleet by 80.2% and 67.7% at the same time. The inclusion of the case study in this paper is essential since it highlights the advantage and usefulness of FairCharge. However, a weakness with this paper is it assumes all electric vehicle drivers will follow the recommendations proposed in the study. This is a weakness because not all drivers follow recommendations in real-world scenarios. This weakness can be resolved by providing some sort of participation incentive for drivers who follow the recommendations.

2.3 Natural disaster risk mitigation methods

The following two studies propose different ideas on mitigating wildfire risk while maintaining customer power demands. The first study [7] proposes a solution on how to prevent wildfires caused by electric grid faults without causing customers to experience power cuts. The solution is an optimization model that can potentially help utilities make short-term operational decisions on which equipment to shut off in order to reduce risk of wildfires while still delivering as much power as possible to the customers. The main strength of this paper is that the optimization model is validated using a Southern California based case study. The results of this case study show that the optimization model was able to reduce both the risk of wildfires and amount of lost power while comparing to the two other approaches used in the case study. This case study is useful since it helps understand the effectiveness of the optimization model in a real-world scenario. A weakness of this study is that it does not consider the impact of additional electric faults that can occur after the power shut-off is already in place. This is a critical edge case that can potentially happen in a real-world event.

Therefore, the optimization model needs to consider this case to be more effective for such scenarios. The second study [8] proposes using infrastructure investments such as solar PV, grid-scale batteries, and line hardening or maintenance measures to support system operations during "Power Safety Power Shutoff" (PSPS) events and reduce both load shedding and wildfire ignition risk. It also introduces a multi-period optimization model which considers line de-energizations that can happen during PSPS events to optimize the types, sizes, and locations of such infrastructure investments. Similar to the first study, the main strength of this paper is the inclusion of a case study to validate the proposed solution. In this study, the model was evaluated using two test cases with actual wildfire risk data from the United States Geological survey and realistic infrastructure parameters. The results of these cases suggest that the model is able to suggest different investment decision for different test cases which indicates the model can be effective for different scenarios. One of the weakness of this study is that a lot of analysis work mentioned in this paper uses a number of simplifications. These simplifications need to be reduced so the model can be more effective for the complexities of the real world.

3 PROPOSED METHOD

This section develops, step by step, the proposed method for assessing the optimal placement of electric vehicle chargers to maximize the coverage of risk for an extreme event.

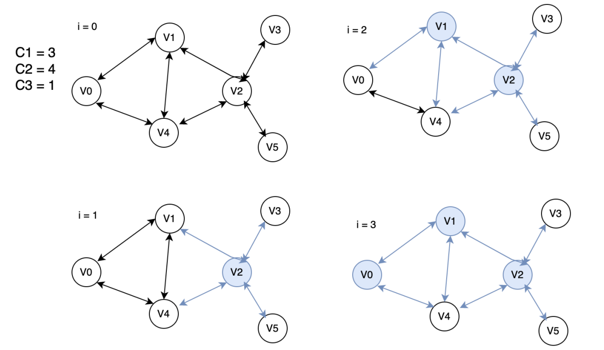

Figure 2: Intuition: basic example network showing coverage with 3 chargers placed. In this case, the greedy algorithm is one of the optimum solutions

3.1 Intuition

3.1.1 Simple example. The intuition of the proposed solution is described via Fig. 2. An infrastructure investor starts with $b = 0$ chargers. **While** number of chargers is less than some threshold $b_{\max}$: the infrastructure planner **adds** the $b + 1$th charger that maximizes the weighted risk coverage. In the case of this small network, this *greedy* approach, which we describe in the subsequent section, is in fact an optimal solution.

3.1.2 Criticality of network edges. We consider an electric power network. Let $\mathcal{E}$ be the set of all conductors (edges) in the network and let $\mathcal{V}$ be the set of all nodes. Where $|\mathcal{E}|$ denotes the number of conductors and $|\mathcal{V}|$ denotes the number of nodes.

Definition 1 (Criticality metric). *An edge $e \in \mathcal{E}$ has a "criticality metric" or weight $w_e \in (0, 1]$. The network has a criticality vector $\mathbf{w} \in (0, 1]^{|\mathcal{E}|}$, where $\mathcal{E}$ is the set of all edges in the network.*

For each edge $e \in \mathcal{E}$, the criticality metric w_e represents the criticality of edge e relative to an extreme event. Concretely, this is the importance of ensuring electric power flow through this edge.

Each node $i \in \mathcal{V}$ can receive **at most one charger.** This motivates the use of *sets* as decision variables. We need to explore *submodular optimization.*

Definition 2 (Charger coverage). *For every node $i \in \mathcal{V}$, let $C_i \subseteq \mathcal{E}$ be the subset of conductors served by a charger at node $i \in \mathcal{V}$. Consider a subset of nodes in the network $\mathcal{S} \subseteq \mathcal{V}$ that receive chargers (i.e., a charger placement "strategy"). We define the coverage of the charger placement strategy $F : 2^{\mathcal{V}} \mapsto \mathbb{R}$ as*

$$F(\mathcal{S}) \triangleq \sum_{e\in\mathcal{E}} w_e \mathbf{1}\left[e \in \bigcup_{i\in\mathcal{S}} C_i\right], \tag{1}$$

where $\mathbf{1}[\cdot]$ is the indicator function.

3.1.3 Coverage matrix. We will represent the coverage function via a *coverage matrix*, which we denote as $\boldsymbol{F} \in \{0, 1\}^{|\mathcal{E}|\times|\mathcal{V}|}$ that is indexed as $(e, v) \in \mathcal{E} \times \mathcal{V}$. We will use values determined by a function $f_{e,v}$ such that $\forall(e,v) \in \mathcal{E} \times \mathcal{V}$:

$$f_{e,v} = \begin{cases} 1 & \text{charger at } v \in \mathcal{V} \text{ services conductor } e \in \mathcal{E}, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

Notice that $f_{e,v} = 1$ is equivalent to the edge being in *coverage set* of node v, i.e., $e \in C_v$, where C_v is the set of all edges (in our case, conductors) whose failure is guaranteed to be prevented by a charger placed at node $v \in \mathcal{V}$.

3.2 Maximizing the coverage under cardinality constraints

Recall that the proposed solution to the problem is to maximize the expected coverage of a proposed charger placement strategy.

3.2.1 Classical greedy approaches. There is a very well-known "greedy" sensor placement algorithm (in our case, a *charger* placement algorithm), derived in [9], that is guaranteed to *approximately* maximize a submodular (i.e., "convex in sets") objective function subject to size constraints on the decision variables.

Theorem 1 (Nemhauser, Wolsey, Fisher '78 [9]). *Let $F : 2^{\mathcal{V}} \mapsto \mathbb{R}$ be a normalized, monotone, submodular function and consider the program*

$$\max_{\mathcal{S} \in 2^{\mathcal{V}}} F(\mathcal{S}) \quad \textit{subject to:} \quad |\mathcal{S}| \leq b. \quad (3)$$

Then there exists a $(1 - \frac{1}{e})$-approximation algorithm, given by Algorithm given below.

The below *greedy* algorithm is *greedy* because it selects the index j that provides the highest increase in $F(\cdot)$ and adds it to the set $\mathcal{S}_i$ for iterations $i \leq b$.

$\mathcal{S} \leftarrow \varnothing$
$i \leftarrow 1$
while $i \leq b$ **do**
  $k_i \leftarrow \arg\max_{j \in \mathcal{V}} f(\mathcal{S}_{i-1} \cap \{j\}) - f(\mathcal{S}_{i-1})$
  $\mathcal{S}_i \leftarrow \mathcal{S}_{i-1} \cap \{k_i\}$
  $i \leftarrow i + 1$
end while

The algorithm in Thm. 1 is well-known and well-established for solving set-theoretic optimization problems. However, it has key limitations. It is not guaranteed to converge, its approximation of the coverage is not accurate, its computational efficiency is extremely slow, and it does not allow for uncertainty in the objective function.

3.2.2 Integer programming approach in this work and evaluation plan. In this work, we will reformulate the algorithm in Thm. 1 via a more modern integer programming (IP) approach, inspired by recent results in [10]. The extension of Thm. 1 in [10] has key advantages, both in computational sense (it is an IP) and a theoretical sense (we can incorporate uncertainty in the objective function). In addition to applying this improved algorithm to electric power network chargers, we will compare this classical approach to a more modern formulation based on integer programming.

3.3 Integer programming formulation

In this section, we describe the basic formulation of the submodular charger placement problem represented through integer programming. We define weighted coverage function $f : \mathbb{Z}^{|\mathcal{E}|} \mapsto \mathbb{R}$ in terms of the resilience matrix $\boldsymbol{F} \in \{0,1\}^{|\mathcal{E}| \times |\mathcal{V}|}$, which accepts an integer variable $\boldsymbol{c} \in \{0,1\}^{|\mathcal{E}|}$, where $\boldsymbol{c}_e = 1$ if some charger $v \in S$ covers edge e, and $\boldsymbol{c}_e = 0$ if there is no charger which covers edge e.

The charger placement decision is formulated in terms of a vector of binary variables $\boldsymbol{x} \in \{0,1\}^{|\mathcal{V}|}$, where $x_v = 1$ if there is a charger at node v and $x_v = 0$ if there is no charger at node v. The number of nonzeros in this vector are constrained to be no greater than b. With all of this information, we can write a preliminary, basic formulation of the charger placement problem as

$$\begin{aligned} \underset{\boldsymbol{c},\boldsymbol{x}}{\text{maximize}} \quad & \sum_{e \in E} w_e c_e && (4a) \\ \text{subject to:} \quad & \boldsymbol{c} \leq F\boldsymbol{x}, && (4b) \\ & \sum_{v \in \mathcal{V}} x_v = b, && (4c) \\ & c_e \in \{0,1\} \quad \forall e \in \mathcal{E}, && (4d) \\ & x_v \in \{0,1\} \quad \forall v \in \mathcal{V}. && (4e) \end{aligned}$$

The constraint (4b) ensures that $c_e = 1$ if some charger $v \in S$ covers edge e, and $c_e = 0$ if there is no charger which covers edge e. If $\boldsymbol{F}_e$ is the e-th row of $\boldsymbol{F}$, then $\boldsymbol{F}_e\boldsymbol{x} = \sum_{v \in \mathcal{V}} x_v \mathbf{1}[e \in C_v]$. That is, $\boldsymbol{F}_e\boldsymbol{x}$ is equal to the number of sensors which cover edge e. We want to ensure that $c_e = 1$ if $\boldsymbol{F}_e\boldsymbol{x} \geq 1$, and 0 otherwise. Therefore, we set the constraint $c_e \leq \boldsymbol{F}_e\boldsymbol{x}$.

Since the function being maximized is a weighted sum of $\boldsymbol{c}$, where all weights are positive, we know at optimality we will have all c_e equal to their upper bound. Therefore, the constraint $c_e \leq \boldsymbol{F}_e\boldsymbol{x}$ achieves $c_e = 1$ if some charger $v \in S$ covers edge e, and $c_e = 0$ if there is no charger which covers edge e.

3.4 Minimax criticality integer programming formulation

3.4.1 Full generality with mixed strategies. Given a maximum number of chargers b, define the set of all feasible charger placement strategies as

$$\mathcal{A} \triangleq \{\mathcal{S} \subseteq \mathcal{V} : |\mathcal{S}| = b\}. \quad (5)$$

We consider the problem of when the grid operator wants to choose a randomized charger placement strategy to minimize the *expected vulnerability* of the edges in the network, where we define the vulnerability of the edge/conductor $e \in \mathcal{E}$ as its criticality w_e times the probability that the edge is unserviced by a charger. The charger placement is then described as a vector in the probability simplex $\sigma \in \Delta(\mathcal{A})$, where

$$\Delta(\mathcal{A}) \triangleq \left\{ \sigma \in \mathbb{R}^{|\mathcal{A}|} | \sum_{\mathcal{S} \in \mathcal{A}} \sigma_{\mathcal{S}} = 1 \text{ and } \sigma_{\mathcal{S}} \geq 0, \ \forall \mathcal{S} \in \mathcal{A} \right\}. \quad (6)$$

Given a fixed strategy $\mathcal{S}$, we define the vulnerability of a conductor e as the criticality times the probability that the conductor is unserviced.

$$w_e(1 - F(\mathcal{S}, \{e\})) \quad (7)$$

where $F(\mathcal{S}, \{e\})$ is defined to be 1 if edge e is covered and 0 otherwise.

Thus, the goal of the grid operator when playing a charger placement strategy $\mathcal{S}$ is to *minimize the maximum expected vulnerability* $K \in \mathbb{R}$ for any edge e, which yields the following primal problem:

$$\min_{\sigma \in \mathbb{R}^{|\mathcal{A}|}, K \in \mathbb{R}} \quad K \quad \text{subject to:} \tag{8a}$$

$$K \geq w_e \sum_{\mathcal{S} \in \mathcal{A}} \sigma_{\mathcal{S}} (1 - F(\mathcal{S}, \{e\})) \quad \forall e \in \mathcal{E} \tag{8b}$$

$$\sum_{\mathcal{S} \in \mathcal{A}} \sigma_{\mathcal{S}} = 1 \tag{8c}$$

$$\sigma_{\mathcal{S}} \geq 0 \quad \forall \mathcal{S} \in \mathcal{A} \tag{8d}$$

where for a vulnerable $e \in \mathcal{E}$, we have that $F(\mathcal{S}, \{e\}) = 0$ if the edge is unserviced by charger set $\mathcal{S}$ and $F(\mathcal{S}, \{e\}) = 1$ if the edge is serviced by charger set $\mathcal{S}$.

3.4.2 Deterministic strategy version. For the purposes of meeting the page limit of this project, we consider the deterministic version of the above problem. The **intuition** is that we want to find the best **maximum** number of chargers to invest in: i.e., b. We use weights w_e on edges $e \in E$ that represent the criticality of e in an **extreme event** (e.g. weather, disaster).

This yields the following *min-max criticality* problem. We want to solve

$$\min \max K = \min \max \sum_e w_e (1 - c_e)$$

.

Such a problem can be formulated as an equivalent integer program (9)

$$\min_{c,x,K} \quad K \quad \text{subject to:} \tag{9a}$$

$$w_e (1 - c_e) \leq K \quad \forall e \in E \tag{9b}$$

$$\sum_{v \in V} x_v = b \tag{9c}$$

$$c \leq Fx \tag{9d}$$

$$c_e \in \{0, 1\} \quad \forall e \in E \tag{9e}$$

$$x_v \in \{0, 1\} \quad \forall v \in V \tag{9f}$$

where:

- w_e is the weight (criticality) of the edge
- F is the coverage matrix (e.g., incidence matrix for simple example here)
- c_e is the coverage of a particular edge. $c_e = 1$ if a charger covers that edge, and 0 otherwise
- x_v is binary, whether or not the vertex was included in the set

4 ELECTRIC POWER NETWORK FORMULATION

We consider an electric power network $\mathcal{G} \triangleq (\mathcal{N}, \mathcal{E})$, where $\mathcal{N} \triangleq \{1, \ldots, n\}$ is the set of measured nodes linked by lines $\mathcal{E} = \{(i, j) \in \mathcal{N} : i \longrightarrow j\}$. The net complex power injections at each node $i \in \mathcal{N}$ of this network are denoted by $p_i + jq_i \in \mathbb{C}$, where p_i is the net active power injection, q_i is the net reactive power injection, and $j \triangleq \sqrt{-1}$. These are related with the bus voltages $\bar{v}_i \triangleq v_i \angle \theta_i \in \mathbb{C}$ and the net current injections $\bar{\ell}_i = \ell_i \angle \phi_i \in \mathbb{C}$ as $p_i + jq_i = \bar{v}_i \bar{\ell}_i^* = \sqrt{p_i^2 + q_i^2} \angle \theta_i - \phi_i$, where $\bar{\ell}_i^*$ is the complex conjugate of the net current injection, $\theta_i - \phi_i$ is the difference between the phase angles of the voltage and current at bus i, and $\sqrt{p_i^2 + q_i^2}$ is the apparent power, i.e., the magnitude of the complex powers.

We consider the set of all *PV nodes* $\mathcal{V} \subseteq \mathcal{N}$, which are the nodes in the network that can possess electric power generators, such as electric vehicle chargers, as we study in this paper. The goal of the proposed solution is to place chargers at nodes $i \in \mathcal{N}$ that minimize the risk of an extreme event. To this end, we study an open-source wildfire risk dataset for the RTS_GMLC network model, that is based on publicly available measurements from the state of California. In Fig. 3, we show an illustration of the publicly available risk heuristic for the nodes of this network model.

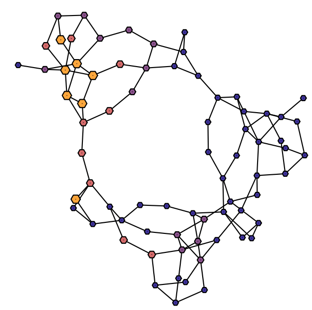

Figure 3: Illustration of nodal wildfire risk heuristic for the RTS_GMLC network model [11] designed in [7]. Warm colors correspond to higher levels of the risk heuristic, while cool colors correspond to lower levels.

4.1 Coverage matrix description

Consider each PV node $v \in \mathcal{V}$ and let $\mathcal{I}(v)$ be the set of incident edges (conductors) on node v. For this midterm milestone report, we will assume *one-hop charging*, i.e., that a charger placed on node $v \in \mathcal{V}$ can serve all incident edges $e \in \mathcal{E}$. This means that the coverage matrix described in Section 3.1.3 is exactly the incidence matrix of the subgraph of the PV nodes $\mathcal{V}$ and the set of all edges that are incident on these nodes.

4.2 Network model description

The proposed method is evaluated using the Grid Modernization Laboratory Consortium Reliability Test System (RTS-GMLC) electric power network dataset [11]. This open-source dataset was developed by the US Department of Energy National Renewable Energy Lab (NREL) [11], and is a realistic grid data model based on an undisclosed town in Southern California. This network model is widely used, and is regarded as a gold standard network model in the electric power systems research community.

4.3 Dataset description

4.3.1 Construction of risk heuristic and criticality weights. We base our risk heuristic off of [7]. We construct this heuristic using the baseline edge risks in the `RTS_GMLC` [11] model (graphically shown in Fig. 3), and the weather-based risks mentioned in Section 4.3. This allows us to formulate the criticality $\boldsymbol{w}^{(t)} \in \mathbb{R}^{|\mathcal{E}|}$ as the baseline power infrastructure risk κ_e times the weather-risk at time t. We have:

$$w_e^{(t)} = \kappa_e r_e^{(t)} \quad \forall e \in \mathcal{E}, \quad \forall t = 1, \ldots, T. \tag{10}$$

4.3.2 Timeseries risk data. We use the rolling time horizon wildfire risk dataset from the public United States Geological Survey, which is described in detail in [8]. This provides *weather-based* risk values $r_e^{(t)} \in (0, 1]$ for each edge $e \in \mathcal{E}$ over times $t = 1, \ldots, T$.

5 EXPERIMENTS, RESULTS AND DISCUSSION

In this report, we consider several scenarios for maximum charging strategy size constraints, specifically, $b = 5, 10, 25, 40$. We then apply the classic iterative algorithm [9] described in Theorem 1 to the dataset outlined above. In the following results, we present the convergence of the algorithm and the wildfire risk coverage of the charger placement strategies at each constraint scenario.

5.1 Experimental hypothesis

The experiments **are designed to answer:**

(1) What is the best placement strategy of chargers on nodes in the network given a maximum number of chargers b?
(2) How do the IP and greedy approaches for answer this question compare?
(3) How can we use the minimax criticality algorithm to assess the best choice of maximum charger constraint b?

5.2 Results and summary of findings

5.2.1 Greedy algorithm coverage and convergence as a function of charger strategy size. In Fig. 4, we show the convergence of the method as a function of the maximum size of the EV charger placement strategy b for a *single point in time* (i.e., a single wildfire risk profile $\boldsymbol{r}_t$ described in Section 4.3) This validates that the wildfire coverage (right) monotonically increases with the size of b, and the algorithm convergence (left) gets arbitrarily better.

5.2.2 Greedy algorithm coverage as a function of time for different charger strategy sizes. In Fig. 5, we show the risk coverage for EV charger placement strategies limited by $b \in \{5, 10, 25, 40\}$ as a function of time. In this experiment, we are using *only* the US Geological Survey data described in Section 4.3—i.e., *no baseline power network risk* κ_e is considered as defined in (10). A key point to note is that there appears to be a clear *diminishing returns in risk coverage* for EV charger placement strategies beyond $b = 25$.

Interpretation and explanation: The diminishing returns characteristic becomes even more apparent when considering the baseline power risk κ_e for each edge $e \in E$ as defined in (10). Fig. 6 shows the *weighted* wildfire risk coverage for charger investment placement strategies of size $b \in \{5, 10, 25, 40\}$. Note that the risk coverage between $b = 40$ and $b = 25$ collapses entirely when considering the baseline risk κ_e of the network edges $e \in E$.

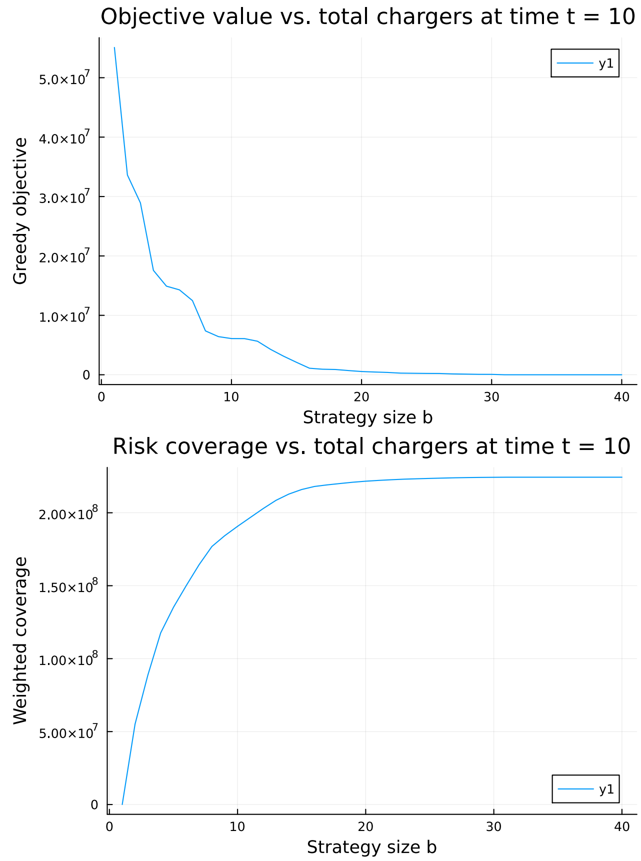

Figure 4: Convergence behavior of Thm. 1 with maximum charger strategy size constraint of $b = 40$. (Top) Greedy objective function value vs. charging strategy size iteration. (Bottom) Weighted wildfire coverage vs. charging strategy size iteration.

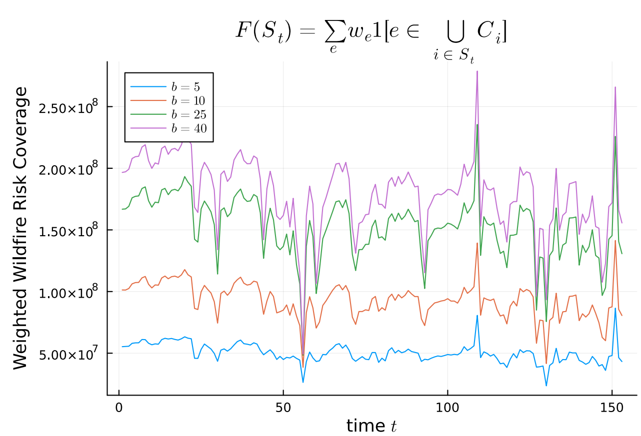

Figure 5: Without base risk κ_e: Wildfire risk coverage for greedy charger placement strategy (Thm. 1) vs. time for the wildfire risk dataset [7] described in Section 4.3. Integer b represents the maximum amount of chargers placed.

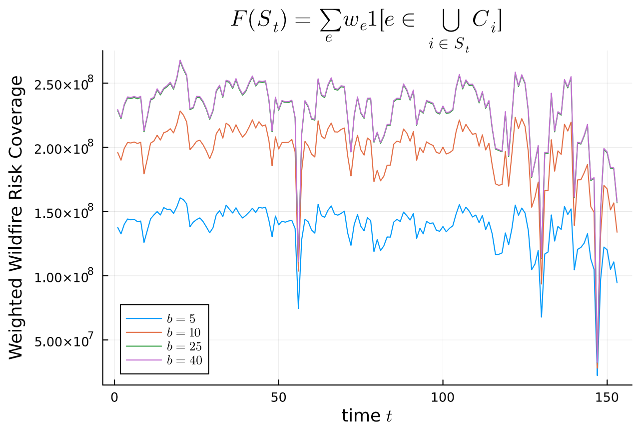

Figure 6: With base risk κ_e: Wildfire risk coverage for greedy charger placement strategy.

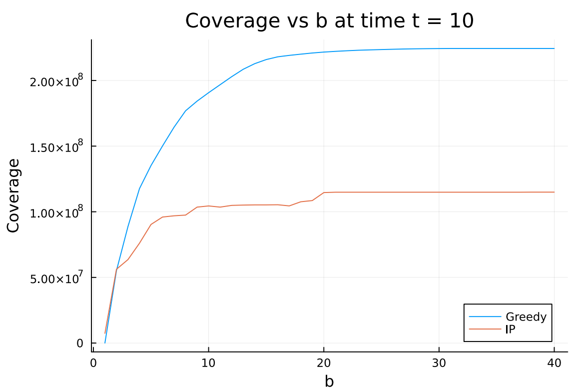

Figure 7: Coverage convergence behavior for the greedy and integer programming algorithm at a selected time point

5.2.3 Comparison of integer programming and greedy approach. In Fig. 7, we compare the greedy approach in Theorem 1 against the integer programming approach in Section 3.3. It can be seen that the greedy algorithm converges to a higher degree of coverage. This is somewhat unexpected behavior—as, empirically, it is typically expected that the IP would yield better results.

Interpretation and explanation: However, this can be interpreted and explained through the fact that neither the IP algorithm nor the greedy algorithm are theoretically guaranteed to converge to a true solution. This indicates that future research is needed to characterize the convergence behavior of the two algorithms and develop guarantees that explain why the results are different, despite the same cardinality constraints.

One possible interpretation is that either the greedy or IP algorithm is not satisfying the constraints of double-counting, and that further improvement in the algorithm is needed.

5.2.4 Minimax criticality evaluation. This section presents results on using the minimax criticality evaluation technique in (9), i.e., the deterministic version. Recall that we observed diminishing returns

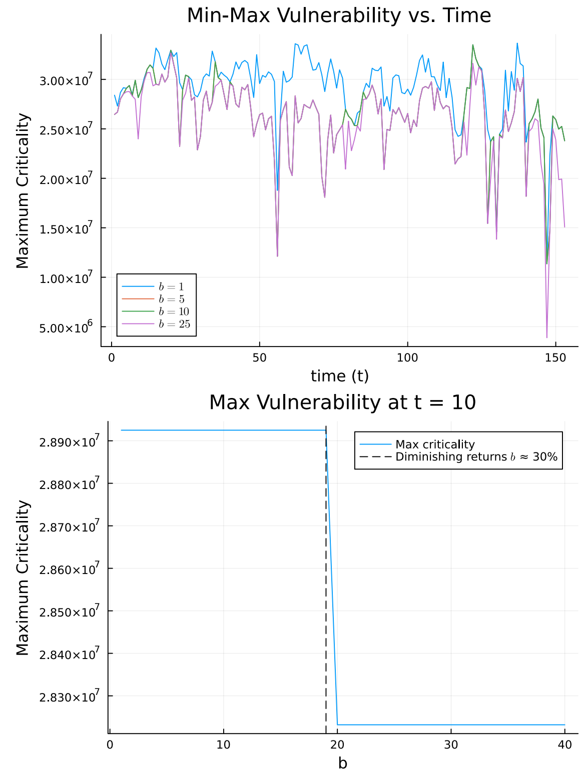

Figure 8: Top: Minimax criticality vs. time for $b \in \{1, 5, 10, 25\}$. Bottom: Example of diminishing returns for a single timestep

in the previous greedy and IP results. This technique seeks to evaluate the diminishing returns. In Fig. 8, we study the diminishing returns using the minimax criticality technique. Specifically, in Fig. 8, we show the minimum maximum criticality for as a function of the maximum number of chargers (bottom) and for selected charger sizes $b \in \{1, 5, 10, 25\}$ vs. time in the top.

Interpretation and explanation: the effects of diminishing returns are verified in Fig. 8 as they show the step change in minimax criticality at $b \approx 20$ as shown before. It also shows that the K vs. time curves become identical as $k \longrightarrow 25$.

6 CONCLUSION, CHALLENGES AND FUTURE WORK

This research presented results on using *network placement* submodular optimization algorithms to "cover" the risk of electric power shutoffs due to wildfires in electric power networks. We used a well-known greedy algorithm and integer programming approach to derive a basic preliminary result. We then developed a post-hoc decision rule using a minimax algorithm in (9) that determines the "point of diminishing returns" for further infrastructure investments.

6.1 Limitations and Future work

6.1.1 Integer programming approach. While past empirical intuition has indicated the IP formulation in Section 3.3. should yield better coverage results than the greedy algorithm, the greedy approach in Theorem 1 outperformed the IP in our experiments.

We hypothesize that this can be interpreted and explained through the fact that neither the IP algorithm nor the greedy algorithm are theoretically guaranteed to converge to a true solution. This indicates that future research is needed to characterize the convergence behavior of the two algorithms and develop guarantees that explain why the results are different, despite the same cardinality constraints.

Another possible interpretation/explanation is that either the greedy or IP algorithm is not satisfying the constraints of double-counting, and that further improvement in the algorithm is needed.

6.1.2 Stochastic IP via column generation. The current version of the min-max criticality problem is done in the non-mixed strategy case, i.e., the strategy is treated as a deterministic binary variable. Future work should apply the column generation algorithm to solve the stochastic version. This will be a highly complex task, and is an active area of research that is a very interesting direction for future work.

6.1.3 Evaluation criteria. Future work should consider criteria in the objective function beyond risk mitigation. Specifically, future work should seek to include social fairness of the charger placement (e.g., as done in [12]), community EV penetration, etc.. We will also consider multi-edge servicing (non-one-hop servicing of the EV chargers), which will represent a more complex problem. Furthermore, future work should investigate the diminishing returns for EV charger placement strategies shown in Fig. 5, and seek to develop heuristics based on the Pareto Front or other similar tools to quantify this.

REFERENCES

[1] K. Feng, N. Lin, S. Xian, and M. Chester, “Can we evacuate from hurricanes with electric vehicles?” *Transportation Research Part D: Transport and Environment*, 2020.

[2] Q. Li, S. Soleimaniamiri, and X. Li, “Optimal mass evacuation planning for electric vehicles before natural disasters,” *Transportation Research Part D: Transport and Environment*, vol. 107, 2022.

[3] A. Y. S. Lam, Y.-W. Leung, and X. Chu, “Electric vehicle charging station placement: Formulation, complexity, and solutions,” *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2846–2856, 2014.

[4] T. D. Chen, K. M. Kockelman, W. Murray, and M. Khan, “The electric vehicle charging station location problem: A parking-based assignment method for seattle,” 2013.

[5] D. L. Donaldson, M. S. Alvarez-Alvarado, and D. Jayaweera, “Power system resiliency during wildfires under increasing penetration of electric vehicles,” in *2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2020, pp. 1–6.

[6] G. Wang, Y. Zhang, Z. Fang, S. Wang, F. Zhang, and D. Zhang, “Faircharge: A data-driven fairness-aware charging recommendation system for large-scale electric taxi fleets,” *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 4, no. 1, mar 2020. [Online]. Available: https://doi.org/10.1145/3381003

[7] N. Rhodes, L. Ntaimo, and L. Roald, “Balancing wildfire risk and power outages through optimized power shut-offs,” *IEEE Transactions on Power Systems*, vol. 36, no. 4, pp. 3118–3128, 2021.

[8] A. Kody, R. Piansky, and D. K. Molzahn, “Optimizing transmission infrastructure investments to support line de-energization for mitigating wildfire ignition risk,” *arXiv preprint arXiv:2203.10176*, 2022.

[9] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher, “An analysis of approximations for maximizing submodular set functions—i,” *Mathematical Programming*, vol. 14, pp. 265–294, 1978.

[10] J. Milošević, M. Dahan, S. Amin, and H. Sandberg, “A network monitoring game with heterogeneous component criticality levels,” in *2019 IEEE 58th Conference on Decision and Control (CDC)*, 2019, pp. 4379–4384.

[11] C. Barrows, A. Bloom, A. Ehlen, J. Ikaheimo, J. Jorgenson, D. Krishnamurthy, J. Lau, B. McBennett, M. O’Connell, E. Preston, A. Staid, G. Stephen, and J.-P. Watson, “The IEEE Reliability Test System: A Proposed 2019 Update,” *IEEE Transactions on Power Systems*, vol. 35, no. 1, Jul. 2019, institution: National Renewable Energy Lab. (NREL), Golden, CO (United States) Number: NREL/JA-6A20-71958 Publisher: IEEE. [Online]. Available: https://www.osti.gov/pages/biblio/1545004

[12] A. Kody, A. West, and D. K. Molzahn, “Sharing the load: Considering fairness in de-energization scheduling to mitigate wildfire ignition risk using rolling optimization,” in *2022 IEEE 61st Conference on Decision and Control (CDC)*, 2022, pp. 5705–5712.

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