

# 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, transportation networks, electric power networks, smart chargers

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## Availability of Data and Material:

The data and code used in this paper will be made publicly available at <https://github.com/samtalki/ChargerPlacement.jl>

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## 1 INTRODUCTION

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.

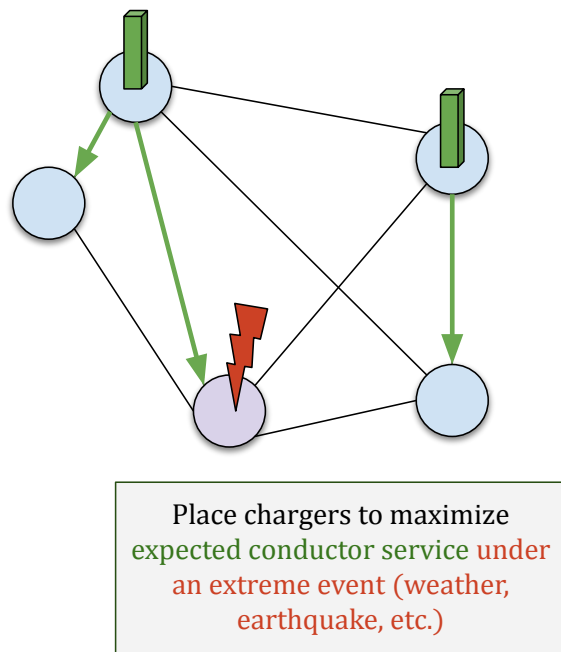
## 2 RESPONSE TO REVIEW COMMENTS

We thank the Professor for the helpful feedback and commentary on the first submission of the manuscript. Below, we address all comments provided.

- (1) Context of whether this is work done for this class:
  - (a) This comment has been addressed via our previous email conversation after the proposal assignment grade release.
- (2) Analyzing results/understanding the strategy/real test case:
  - (a) We have found a real case to analyze the results, based on [1–3]. This provides a real-world example of the strategy we are picking (wildfire resilience mitigation) based on the real-world data provided by Rhodes et al. in [2]. We describe this case in Section 5, with results in Section 6.

## 3 BACKGROUND

There have been two main studies in the past regarding evacuation from natural disasters using electric vehicles. One of the studies



**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.**

[4] 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 this study suggest that Florida would face serious challenge in power supply if the majority of evacuating vehicles are electric vehicles. The main strength of this study is that several edge cases and situations are considered when describing the specific Florida case study. For instance, 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. The second study [5] 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 departure 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 known 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 evacuation 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.

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 [6], yet there have been attempts to find heuristic solutions. Lam et al [7] 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 [8] 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 [9] 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.

The following two studies propose different ideas on mitigating wildfire risk while maintaining customer power demands. The first study [2] 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 [3] 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.

## 4 THEORETICAL BACKGROUND

### 4.1 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  $S \subseteq \mathcal{V}$  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*

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

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

### 4.2 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.

**4.2.1 Classical greedy approaches.** There is a very well-known "greedy" sensor placement algorithm (in our case, a *charger* placement algorithm), derived in [10], 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 [10]).** *Let  $F : 2^{\mathcal{V}} \mapsto \mathbb{R}$  be a normalized, monotone, submodular function and consider the program*

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

*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  $S_i$  for iterations  $i \leq b$ .

```

S ← ∅
i ← 1
while i ≤ b do
    k_i ← arg max_{j ∈ V} f(S_{i-1} ∪ {j}) - f(S_{i-1})
    S_i ← S_{i-1} ∪ {k_i}
    i ← 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.

**4.2.2 New 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 [11]. The extension of Thm. 1 in [11] 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.

### 4.3 Coverage matrix

We will assume access to a *coverage matrix*, which we denote as  $F \in \{0, 1\}^{|\mathcal{E}| \times |\mathcal{V}|}$  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  $\forall(e, v) \in \mathcal{E} \times \mathcal{V}$ :

$$f_{e,v} = \begin{cases} 1 & \text{charger at } v \in \mathcal{V} \text{ services conductor } e \in \mathcal{E}, \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

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  $v \in \mathcal{V}$ .

#### 4.4 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  $F \in \{0, 1\}^{|\mathcal{E}| \times |\mathcal{V}|}$ , which accepts an integer variable  $\mathbf{c} \in \{0, 1\}^{|\mathcal{E}|}$ , where  $c_e = 1$  if some charger  $v \in S$  covers edge  $e$ , and  $c_e = 0$  if there is no charger which covers edge  $e$ .

The charger placement decision is formulated in terms of a vector of binary variables  $\mathbf{x} \in \{0, 1\}^{|\mathcal{V}|}$ , 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

$$\text{maximize}_{\mathbf{c}, \mathbf{x}} \quad \sum_{e \in \mathcal{E}} w_e c_e \quad (4a)$$

$$\text{subject to: } \mathbf{c} \leq F\mathbf{x}, \quad (4b)$$

$$\sum_{v \in \mathcal{V}} x_v = b, \quad (4c)$$

$$c_e \in \{0, 1\} \quad \forall e \in \mathcal{E}, \quad (4d)$$

$$x_v \in \{0, 1\} \quad \forall v \in \mathcal{V}. \quad (4e)$$

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  $F_e$  is the  $e$ -th row of  $F$ , then  $F_e \mathbf{x} = \sum_{v \in \mathcal{V}} x_v \mathbf{1}[e \in C_v]$ . That is,  $F_e \mathbf{x}$  is equal to the number of sensors which cover edge  $e$ . We want to ensure that  $c_e = 1$  if  $F_e \mathbf{x} \geq 1$ , and 0 otherwise. Therefore, we set the constraint  $c_e \leq F_e \mathbf{x}$ .

Since the function being maximized is a weighted sum of  $\mathbf{c}$ , where all weights are positive, we know at optimality we will have all  $c_e$  equal to their upper bound. Therefore, the constraint  $c_e \leq F_e \mathbf{x}$  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  $e$ .

#### 4.5 Stochastic integer programming formulation

Given a maximum number of chargers  $b$ , define the set of all feasible charger placement strategies as

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

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 unserved by a charger. The charger placement is then described as a vector in the probability simplex  $\sigma \in \Delta(\mathcal{A})$ , where

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

Given a fixed strategy  $S$ , we define the vulnerability of a conductor  $e$  as the criticality times the probability that the conductor is unserved.

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

where  $F(S, \{e\})$  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  $S$  is to *minimize the maximum expected vulnerability*  $K \in \mathbb{R}$  for any edge  $e$ , which yields the following primal problem:

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

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

$$\sum_{S \in \mathcal{A}} \sigma_S = 1 \quad (8c)$$

$$\sigma_S \geq 0 \quad \forall S \in \mathcal{A} \quad (8d)$$

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

### 5 ELECTRIC POWER NETWORK FORMULATION

We consider an electric power network  $\mathcal{G} \triangleq (\mathcal{N}, \mathcal{E})$ , where  $\mathcal{N} \triangleq \{1, \dots, n\}$  is the set of measured nodes linked by lines  $\mathcal{E} = \{(i, j) \in \mathcal{N} : i \rightarrow j\}$ . 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. 2, we show an illustration of the publicly available risk heuristic for the nodes of this network model.

#### 5.1 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 4.3 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.

#### 5.2 Dataset description

We use the rolling time horizon wildfire risk dataset from the public United States Geological Survey, which is described in detail in [3]. This provides *weather-based* risk values  $r_e^{(t)} \in (0, 1]$  for each edge  $e \in \mathcal{E}$  over times  $t = 1, \dots, T$ .

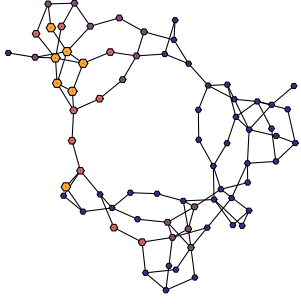


Figure 2: Illustration of nodal wildfire risk heuristic for the RTS\_GMLC network model [1] designed in [2]. Warm colors correspond to higher levels of the risk heuristic, while cool colors correspond to lower levels.

### 5.3 Construction of risk heuristic and criticality weights

We base our risk heuristic off of [2]. We construct this heuristic using the baseline edge risks in the RTS\_GMLC [1] model (graphically shown in Fig. 2), and the weather-based risks mentioned in Section 5.2. This allows us to formulate the criticality  $w^{(t)} \in \mathbb{R}^{|\mathcal{E}|}$  as the baseline power infrastructure risk  $\kappa_e$  times the weather-risk at time  $t$ . We have:

$$w_e^{(t)} = \kappa_e r_e^{(t)} \quad \forall e \in \mathcal{E}, \quad \forall t = 1, \dots, T. \quad (9)$$

## 6 CONCLUSION, PRELIMINARY RESULTS, AND NEXT DIRECTIONS

In this midterm report, we consider several scenarios for maximum charging strategy size constraints, specifically,  $b = 5, 10, 25, 40$ . We then apply the classic iterative algorithm [10] 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.

### 6.1 Summary of results

**6.1.1 Greedy algorithm coverage and convergence as a function of charger strategy size.** In Fig. 3, 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  $r_t$  described in Section 5.2). This validates that the wildfire coverage (right) monotonically increases with the size of  $b$ , and the algorithm convergence (left) gets arbitrarily better.

**6.1.2 Greedy algorithm coverage as a function of time for different charger strategy sizes.** In Fig. 4, we show the risk coverage for EV charger placement strategies limited by  $b = 5, 10, 25, 40$  as a function of time, using the US Geological Survey data described in Section 5.2. A key point to note is that there appears to be a clear *diminishing returns* in risk coverage for EV charger placement strategies beyond  $b = 25$ . This is a key area to investigate in future work.

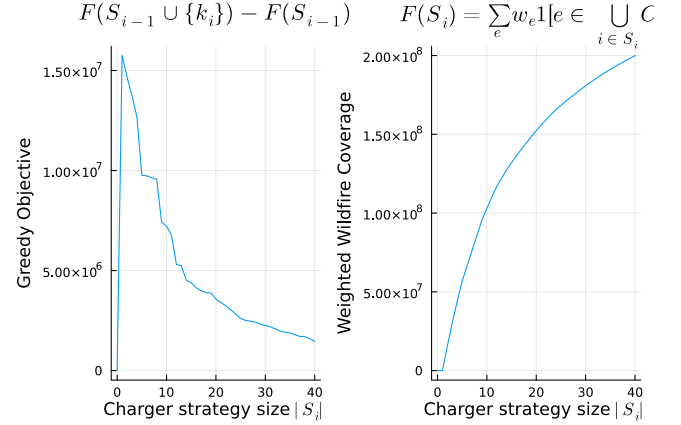


Figure 3: Convergence behavior of Thm. 1 with maximum charger strategy size constraint of  $b = 40$ . (Left) Greedy objective function value vs. charging strategy size iteration. (Right) Weighted wildfire coverage vs. charging strategy size iteration.

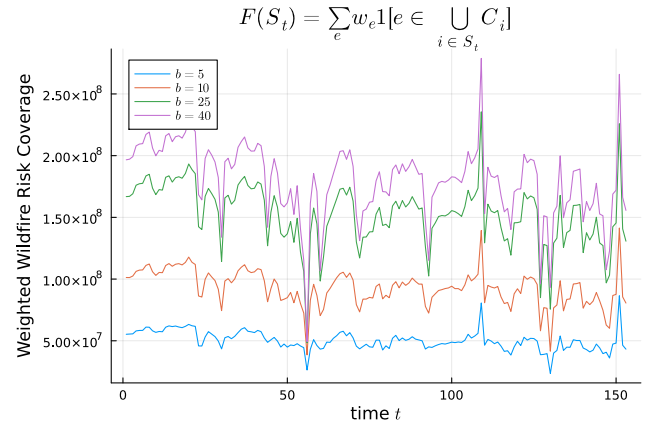


Figure 4: Wildfire risk coverage for greedy charger placement strategy (Thm. 1) vs. time for the wildfire risk dataset [2] described in Section 5.2. Integer  $b$  represents the maximum amount of chargers placed.

### 6.2 Challenges and next steps to complete

**6.2.1 Integer programming experiments.** We need to apply the integer programming methods discussed in Section 4.4. The next report will include results with the deterministic and stochastic integer programming formulations in equations (4) and (8), respectively.

**6.2.2 Evaluation criteria.** The next report will include preliminary results for including other criteria into the objective function beyond risk mitigation. Specifically, we will 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, we will investigate the diminishing returns for EV charger placement strategies shown in Fig. 4, and seek to develop heuristics based on the Pareto Front or other similar tools to quantify this.

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