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 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 event 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 BACKGROUND

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 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

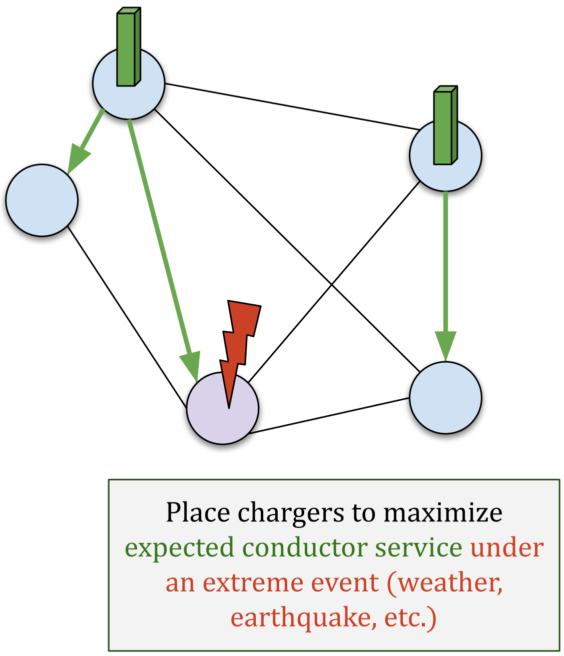

Figure 1: Illustration of the proposed problem and solution: optimal placement of electric vehicle chargers in an electric power network for resilience to an extreme weather event.

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. These solutions include developing centralized charging strategies, improving battery technology, and adopting hybrid vehicles along with EVs. 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 also 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 [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 to each other since both try to answer the main question of whether mass evacuation from natural disasters using EVs is possible. However, as previously mentioned, they differ from each other in the way they answer this question. The first paper comments on the possibility through a case study. Using this, it answers whether successful evacuation is possible. The second paper answers the question by not only clarifying the possibility of successful evacuation from natural disasters using EVs but also 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 [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.

3 FORMULATION

3.1 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 $\boldsymbol{w} \in (0,1]^{|\mathcal{E}|}$, 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*

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

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 [7], 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 [7]). *Let $F : 2^{\mathcal{V}} \mapsto \mathbb{R}$ be a normalized, monotone, submodular function and consider the program*

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

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 $\mathcal{S}_i$ 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 *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 [8]. The extension of Thm. 1 in [8] 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 Coverage matrix

We will assume access to a *resilience matrix* of the form $\boldsymbol{F} \in \{0,1\}^{|\mathcal{E}| \times |\mathcal{V}|}$ 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 $\forall (e, v) \in \mathcal{E} \times \mathcal{V}$:

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

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 $v \in \mathcal{V}$.

3.4 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 $\boldsymbol{F} \in \{0,1\}^{|\mathcal{E}| \times |\mathcal{V}|}$, 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

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

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.

3.5 Stochastic integer programming formulation

3.5.1 (h) Randomized Strategy. Given a maximum number of chargers b, define the set of all feasible charger placement strategies as

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

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

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

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

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

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 $\mathcal{S}$.

4 NEXT STEPS AND DISCUSSION

4.1 Dataset development

The proposed project will be based on the Grid Modernization Laboratory Consortium Reliability Test System (`RTS-GMLC`) electric power network dataset [9]. This open-source dataset was developed by the US Department of Energy National Renewable Energy Lab (NREL) [9], and is a realistic grid data model based on an undisclosed town in Southern California. This dataset is a widely used, gold standard in the electric power systems research community.

Furthermore, we will use the open-source `PowerModels.jl` [10] Julia language package to model and interface with the `RTS-GMLC` dataset. `PowerModels.jl` allows for rapid and realistic simulations of electric power network datasets, and allows for the user to make predictions about changes in the data based on the physical power flow equations. This package also has native, in-built compatibility with the JuMP [11] modeling language, which we will use to solve our optimization problem.

4.2 Projected Accomplishments by End of Semester

By the end of the semester, the following goals will be accomplished in this project:

(1) The proposed algorithm will be implemented as a integer programming algorithm in the JuMP optimization modeling language [11] using the Gurobi integer programming solver.
(2) The proposed method will be developed by synthesizing the algorithm with a power network simulator, namely, the well-known electric power network optimization package in the Julia programming language known as `PowerModels.jl` [10].
(3) The proposed method will be released publicly on GitHub under the MIT or BSD license.
(4) The proposed method will result in a conference paper that is intended to be submitted to the 57th Hawaii International Conference on System Sciences (HICSS). The call for papers is available at: https://hicss.hawaii.edu/. This conference has a submission deadline of *June 15th, 2023*.

4.3 Project Work Split Details

The group for this project consists of Utkarsh (horizontal student), Hassan (horizontal student), and Samuel (vertical student). As horizontal students, Hassan and Utkarsh will be handling the synthetic dataset prepared by Samuel and conducting analysis and developing visualizations using the dataset. They will also be assisting Samuel with some parts of the vertical related works (such as dataset acquisition and designing the integer programming algorithm). Samuel will work on the modeling and optimization of the integer problem.

4.4 Timeline

(1) Feb. 23-Mar. 13: Implementation of charger placement game in the JuMP optimization modeling language [11].
(2) Mar. 13-Mar. 23: Preparation and submission of project milestone report.
(3) Mar. 23-Apr. 10: Testing of charger placement game the publicly available RTS-GMLC [9] electric power network dataset.
(4) Apr. 10-Apr. 20: Preparation and submission of final report and slides.
(5) Apr. 20-Apr. 25: Delivery of final presentation.
(6) Apr. 25-May 25: Extension of project into full conference paper format.
(7) May 25-June 15: Revision of conference paper,
(8) June 15: Submission of conference paper to HICSS conference.

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] 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.

[8] 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.

[9] 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

[10] C. Coffrin, R. Bent, K. Sundar, Y. Ng, and M. Lubin, "PowerModels.jl: An Open-Source Framework for Exploring Power Flow Formulations," in *2018 Power Systems Computation Conference (PSCC)*, June 2018, pp. 1–8.

[11] I. Dunning, J. Huchette, and M. Lubin, "Jump: A modeling language for mathematical optimization," *SIAM Review*, vol. 59, no. 2, pp. 295–320, 2017.