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

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Motivation

Efficient evacuation procedures in urban environments are crucial for ensuring public safety. With the increase in electric vehicles in roadways, it is essential to explore ways to maximize the expected ability for successful evacuation in the event of an emergency.

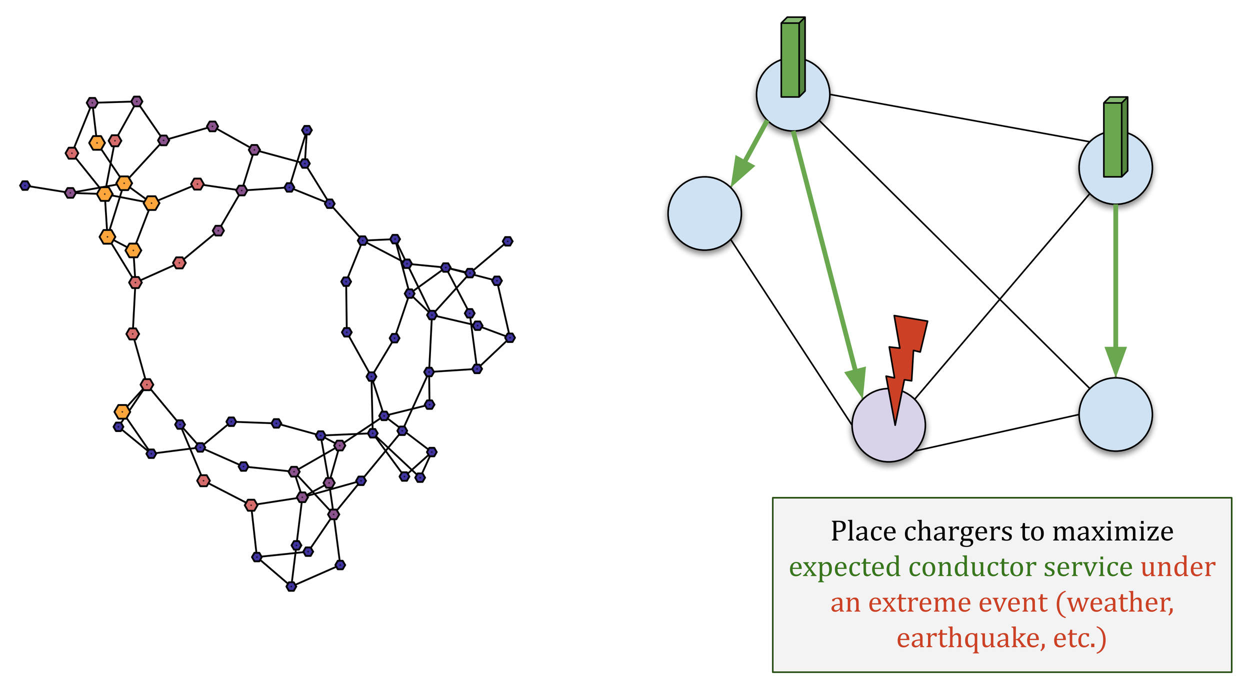

Figure 1. High level description of the proposed problem (left) and solution(right)

The proposed solution (shown above) to this problem is based on a submodular optimization framework to determine the optimal set of locations for placing the chargers. The method accounts for factors such as the distribution of at-risk populations, and the availability of evacuation routes.

Related Work

Past work [1, 3] studied evacuation from natural disasters using electric vehicles. Below are some opportunities for extending these studies:

- [1] confirms the possibility of successful evacuation but does not provide evacuation planning
- [3] assumes the charging station availability is known during the planning stage (This problem is addressed by this work)

Data

- Grid Modernization Lab Consortium Reliability Test System (RTS-GMLC) network model
  - Public, gold standard network model
  - Based on real-world network in Southern California
- Risk weights for RTS-GMLC by [6] (Public, based on gold standard network model)
- Rolling time horizon wildfire risk dataset from the public United States Geological Survey, described in [2] (Public, cleaned JLD5 dataset shared by authors of [2].)

Generate *weather-based* risk values $r_e^{(t)} \in (0,1]$ for each edge $e \in E$ over times $t = 1, \dots, T$. Network model in Fig. 1 shows nodal wildfire risk heuristic for the RTS_GMLC network model. Warm colors mean higher levels of risk while cool colors mean lower levels of risk.

Derive the criticality of an edge (w_e) as the baseline edge risks (k_e) times the weather-risk at time t.

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

Proposed Approach

This problem is modeled similarly to the sensor placement problem, instead here we are trying to maximize the coverage of the set of chargers. There exists a well studied greedy approach that provides a $(1 - \frac{1}{e})$ approximation to the optimal solution [5] but has a few drawbacks:

- Its not guaranteed to converge
- Its approximation of the coverage is not accurate
- Its computational efficiency is slow

To overcome these we plan to implement a more modern integer programming (IP) approach. This has theoretical and computational advantages over the greedy algorithm [4].

1. Greedy Algorithm

Start with $b = 0$ chargers. **While** number of chargers is less than some threshold $b_{\max}$: **add** the $b + 1$th charger that maximizes the coverage

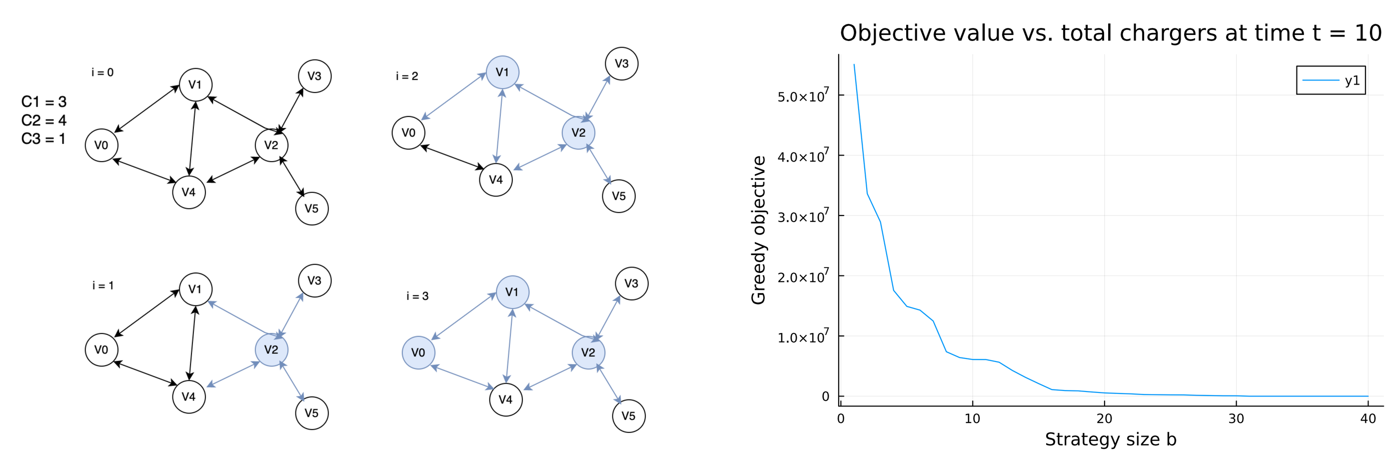

Figure 2. Left: Basic example network showing coverage with 3 chargers placed. In this case, the greedy algorithm is one of the optimum solutions. Right: Greedy objective convergence example.

2. Post-hoc Minimax Criticality

Finding the best number of chargers to invest in b is tackled using integer programming (IP).

Use weights w_e on edges $e \in E$ that represent the criticality of e in an **extreme event** (e.g. weather, disaster).

Min-max criticality: Solve $\min\max K = \min\max \sum_e w_e(1 - c_e)$. **Equivalent IP:**

$$\min_{c,x,K} \quad K \quad \text{subject to:} \tag{1a}$$
$$w_e(1 - c_e) \le K \quad \forall e \in E \tag{1b}$$
$$\sum_{v \in V} x_v = b \tag{1c}$$
$$c \le Fx \tag{1d}$$
$$c_e \in \{0,1\} \quad \forall e \in E \tag{1e}$$
$$x_v \in \{0,1\} \quad \forall v \in V \tag{1f}$$

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

Experiments and Results

Compute risk coverage for varying charger investments, assess using min-max criticality algorithm

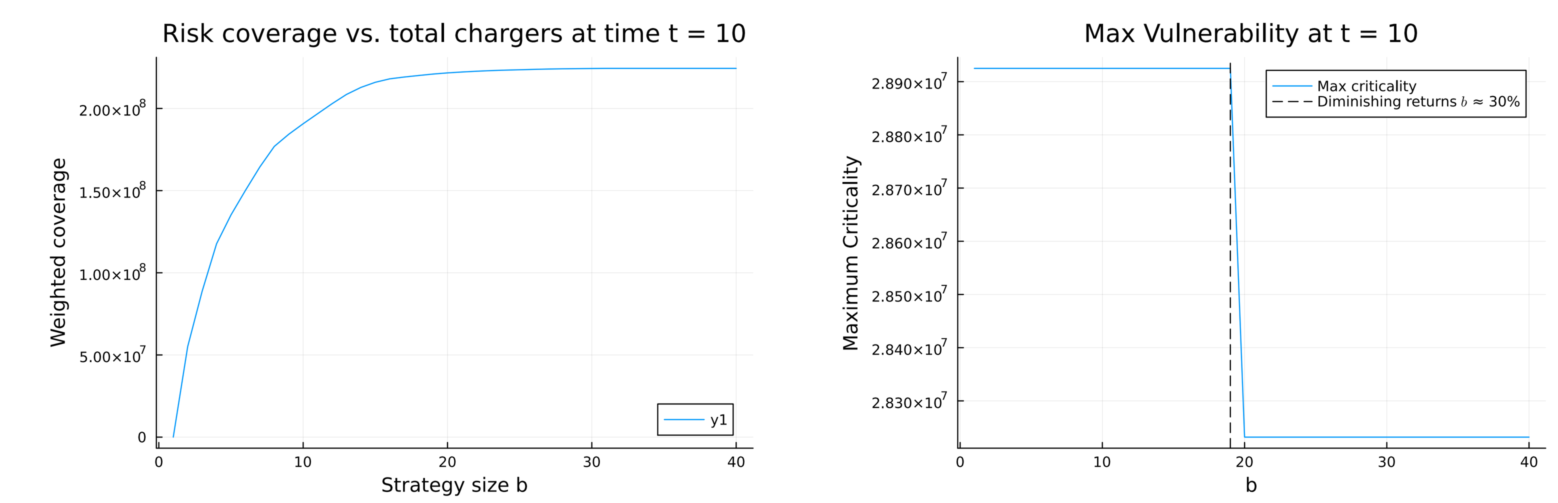

Figure 3. Left: Greedy coverage via [5]. Right: example of diminishing returns for a single timestep (right)

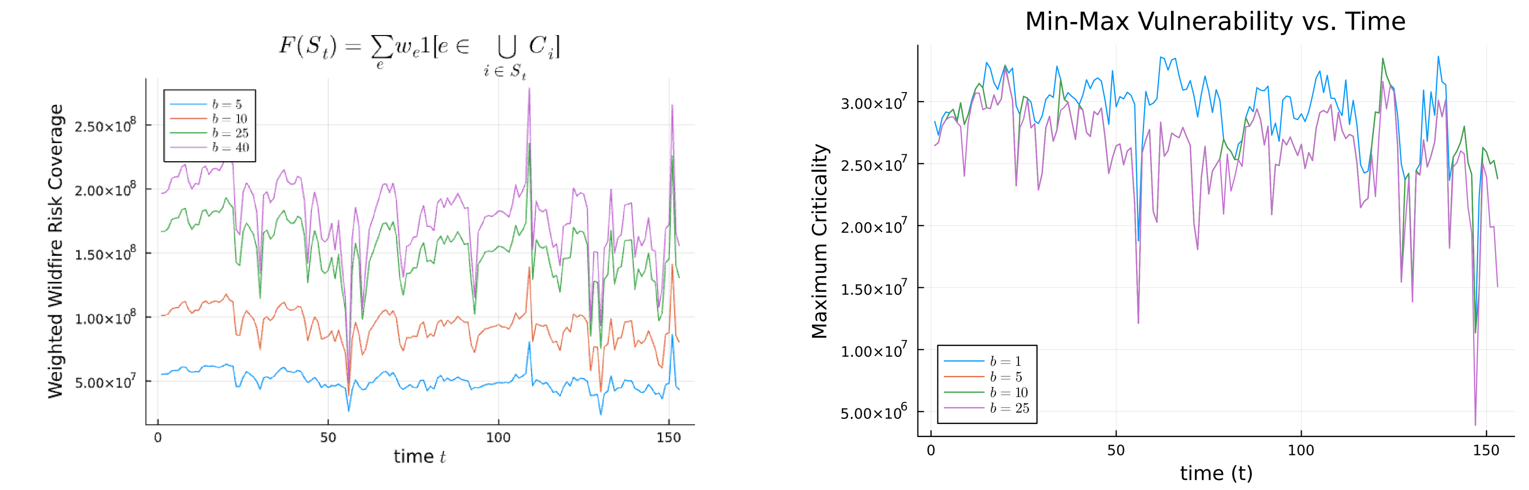

Figure 4. Time-series coverage (left) and min-max criticality (right)

Diminishing returns in risk coverage for more than $b \approx 20 \approx 0.3|V|$ EV chargers placed. Solves current literature gap [3].

Summary of Findings and Conclusion

1. Network placement algorithms can improve transportation resilience
2. Empirical *diminishing returns or saturation* behavior is empirically observed at $b \approx 0.3|V|$
3. Min-max criticality approach can find the minimum number of chargers needed for handling the *worst case scenario* of the edges being covered.

References

[1] Kairui Feng, Ning Lin, Siyuan Xian, and Mikhail Chester. Can we evacuate from hurricanes with electric vehicles? *Transportation Research Part D: Transport and Environment*, 2020.

[2] Alyssa Kody, Ryan Piansky, and Daniel K Molzahn. Optimizing transmission infrastructure investments to support line de-energization for mitigating wildfire ignition risk. *arXiv preprint arXiv:2203.10176*, 2022.

[3] Qianwen Li, Saeid Soleimaniamiri, and Xiaopeng Li. Optimal mass evacuation planning for electric vehicles before natural disasters. *Transportation Research Part D: Transport and Environment*, 107, 2022.

[4] Jezdimir Milošević, Mathieu Dahan, Saurabh Amin, and Henrik Sandberg. A network monitoring game with heterogeneous component criticality levels. In *2019 IEEE 58th Conference on Decision and Control (CDC)*, pages 4379–4384, 2019.

[5] George L. Nemhauser, Laurence A. Wolsey, and Marshall L. Fisher. An analysis of approximations for maximizing submodular set functions—i. *Mathematical Programming*, 14:265–294, 1978.

[6] Noah Rhodes, Lewis Ntaimo, and Line Roald. Balancing wildfire risk and power outages through optimized power shut-offs. *IEEE Transactions on Power Systems*, 36(4):3118–3128, 2021.

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