OptICS-EV: A Data-Driven Model for Optimal Installation of Charging Stations for Electric Vehicles *

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Abstract. As the demand for electric vehicles continues to surge worldwide, it becomes increasingly imperative for the government to plan and anticipate its practical impact on society. In particular, any city/state needs to guarantee sufficient and proper placement of charging stations to service all current/future electric vehicle adopters. Furthermore, it needs to consider the inevitable additional strain these charging stations put on the existing power grid. In this paper, we use data-driven models to address these issues by providing an algorithm that finds optimal placement and connections of electric vehicle charging stations in the state of Virginia. Specifically, we found it suffices to build 10,733 additional charging stations to cover 75% of the population within 0.33 miles (and everyone within 2.5 miles). We also show optimally connecting the stations to the power grid significantly improves the stability of the network. Additionally, we study 1) the trade-off between the average distance a driver needs to travel to their nearest charging station versus the number of stations to build, and 2) the impact on the grid under various adoption rates. These studies provide further insight into various tools policymakers can use to prepare for the evolving future.

Keywords: Electric Vehicle · Charging Station Placement · Power Grid.

1 Introduction

The transportation sector is responsible for 17% of the total GHG emissions, of which 41% of emissions come from passenger cars[1]. Thus, reducing carbon footprint has become a critical goal in the transportation domain. Electric vehicles (EV) are a robust solution to addressing this problem given their eco-friendly characteristics. In recent years, the U.S. has witnessed widespread adoption of

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[1] https://www.statista.com/statistics/1185535/transport-carbon-dioxide-emissions-breakdown/

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EVs in the residential sector[2]. Multiple incentives, policy changes, rising fuel prices, and improvements in the range of EVs are some of the influential factors for a rapid increase in EV adoption. Thus, many entities such as urban planners, government, and utilities are increasingly interested in finding optimal placement of EV charging stations (EVCS). Existing research works have focused on optimal EVCS placement with the goal of minimizing total construction cost [20], transportation and substation energy loss [17], or considering driver preferences [21]. Two common goals are (i) supporting consumer charging demand and, (ii) maintaining power grid reliability.

In general, users prefer to be within a reasonable distance of a charging station [7]. In reality, however, it might be impossible to accomplish such a guarantee for everyone, especially in less densely populated areas. Thus, one may impose a much larger upper bound on the maximum distance while minimizing the average across all users. To ensure grid reliability, the new charging stations should be connected to the power network in a way so that the voltages at nodes across the network are within acceptable engineering standard (e.g. 0.9-1.1 per unit (p.u.) for rated voltage of 1 p.u. [3] implying a maximum allowable voltage deviation of 0.1 p.u.). One can accomplish this by connecting new charging stations directly to the closest substation but this incurs additional costs due to long connecting lines. Hence, another realistic goal is to minimize the connection cost (or equivalently, connection distance) of new charging stations to the power grid while ensuring that the node voltages adhere to engineering standards of a reliable power grid. Formally, the problem can be stated as follows:

Problem 1. Given the locations of EV users and the associated power grid, let $d_{max}, d_{avg}, \Delta v$ be constants. Find locations to build and connect EVCS to the grid that minimizes the total connection cost while ensuring that all EV users are within d_{max} to some station, the overall average distance for clients are within d_{avg} and, the voltage deviation at any node in the network is within Δv.

1.1 Our Contributions

1. We present a scalable two-part algorithm that tackles this multi-objective problem in stages. The first part efficiently computes the best placements of charging station to cover the population within the shortest distance possible by iteratively solving an integer program (Section 3.1).
2. The second part aims to ease the potential strain to the power grid after building new charging stations. We formulate an integer problem (7) to find the optimal way to connect the stations to the power grid. This provides essential factors to consider for policymakers when preparing for the surge in power consumption (Section 3.2).
3. We show that, in the first part of the algorithm, we can efficiently find a solution, consisting of 10,733 new charging stations, that covers 75% of the population within 0.33 miles and guarantees everyone is within 2.5 miles

[2] https://afdc.energy.gov/data/10962

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of a charging station. We also demonstrate a trade-off between the average distance of a user to its nearest EVCS and the number of EVCS.

4. For the second part, we consider synthetically created power networks of Virginia [25] and focus on networks in the Montgomery County to show the effect of different adoption scenarios. In particular, it reveals the reduced reliability of the network at high adoption rates. However, an optimal routing algorithm to connect the newly constructed charging stations to the power grid can ensure higher level of reliability.

2 Related Work

Existing works in the literature have addressed the problem of optimal placement of EV charging stations. A detailed review of such works has been done in [2].

In general, flow-capturing models [9,18,33,13] are popular in literature. They model the charging demand as a directed flow along consumer routes of travel in the transportation network and optimally place stations along the routes to cover the demands. Another class of models is the set covering model [31,8]. They model demand locations as polygons or aggregated points and optimally place EVCS facilities to cover the demand locations (located within a threshold distance). Vehicle movement simulation models [7,16] develop activity simulation frameworks. This class of models evaluate the feasibility of daily travel activities of EV owners, given a selection of EVCS locations in the region.

The impact on the voltage profile, phase imbalance, and power quality due to residential EV charging on the power distribution network is studied in [26]. In another work, Gupta et al. [21] pose the optimal EVCS location problem in the context of an oligopolistic market instead of an urban system planner. The work considers locational marginal prices (LMPs, which are the wholesale electricity rate) and uses a penalty function for introducing grid instabilities. A methodology to compute an optimal EV charging network that maximizes profit and satisfies grid constraints, space limitations, and considers time-varying charging demand is proposed in [34]. A post-processing algorithm known as *Removing and Merging Possible Locations algorithm* is proposed to improve the total profit by excluding and merging some of the initial choices made. The problem of simultaneous allocation of EVCS location is considered in [22] from the perspective of a social or urban planner (minimizing social costs, maximizing environmental benefits, and minimizing power losses). The distribution of EV arrivals is estimated from the distribution of vehicle parking times at different parking lots and on different days of the week. The problem of optimal allocation of EVCSs in a balanced [11] and unbalanced [27] radial distribution grid is done where the loss in the power grid and voltage deviation is minimized.

3 Methodology

We tackle the complex Problem 1 by splitting it into two natural components: (i) placing charging stations to cover existing and future EV users, and (ii) connecting the charging stations to the power-grid (Section 3.1, 3.2 respectively).

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3.1 EV Charging Station Placement

We formally define the EV charging station placement problem as follows:

Problem 2. Let C be a set of existing and potential EV users, S_{cur} a set of existing EVCS, S_{cand} a set of candidate locations for placing new EVCS, and distance thresholds d_{max} and d_{avg}. Find the smallest set $S_{new} \subseteq S_{cand}$ such that every user $u \in C$ has a charging station within d_{max} and the average distance between users and their nearest charging station is at most d_{avg}.

Problem 2 is a variation of the classic well-known NP-hard facility location problem. Even though approximation schemes exist [4,10,19], it is not clear if they are computationally feasible in practice. Furthermore, constant approximation might not be desirable either; for example, one may be willing to walk half a mile but not one mile to charge their car and, the cost of building 10,000 and 20,000 charging stations may differ significantly. Thus, we propose an alternative problem. Instead of ensuring the average distance is below some threshold, we introduce multiple thresholds and attempt to cover as much of the population as possible within the lowest threshold possible. For example, due to geographic and personal preferences, we discover three categories of distances, $< 0.25, < 0.5, < 2.5$ miles, the population are willing to travel to charge their car. First, we attempt to cover as many people as possible within 0.25 miles, then 0.5 mile and lastly 2.5 miles. This in turn also ensures a small average distance. To formally define our problem, we first introduce the following definition:

Definition 1. *Let S denote a set of charging stations, and $D = \{d_1, d_2, ..., d_k\}$ be a set of distances. We say, $coverage(u, S, D) = d_i$ if $d_i \in D$ is the smallest distance such that there exists a charging station $s \in S$ where $distance(u, s) \leq d_i$.*

Given these thresholds D, a natural constraint to impose is to ensure that if an user can be covered within distance d_i, it must be covered within distance d_i by the final solution as well. Then, our problem is the following:

Problem 3 (EV Charging Station Placement Problem (EVCSPP)). Let C denote a set of existing and potential EV users, S_{cur} a set of existing charging stations, S_{cand} a set of candidate locations for placing new charging stations, and $D = \{d_1, d_2, ..., d_k\}$ a set of distances where $d_1 < d_2 < ... < d_k$. Find the smallest set $S_{new} \subseteq S_{cand}$ so that $coverage(u, S_{cur} \cup S_{new}, D) = coverage(u, S_{cur} \cup S_{cand}, D)$ for every EV user $u \in C$.

A special case of Problem 3 is when we have a single threshold value d_{th} within D, i.e. $D = \{d_{th}\}$. To ensure a feasible solution exists in this special case, we may assume that for every EV user $u \in C$, there exists a station $s \in S_{cur} \cup S_{cand}$ such that $distance(u, s) \leq d_{th}$. This problem is known to be NP-hard to approximate to a small factor (1.46) [10]. We formulate it as an Integer Program (IP) and use known solvers to obtain a good solution. Consider the following IP (notations within the program are described in Table 1).

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$$\min_{x,y} \quad \sum_{j \in S} y_j \tag{1}$$

$$s.t. \quad \sum_{j \in \mathcal{S}_i} x_{i,j} \geq 1 \qquad \forall i \in C \tag{2}$$

$$x_{i,j} \leq y_j \qquad \forall i, j \tag{3}$$

Table 1: IP (1–3) notations and descriptions of the objective and constraints.

Notation	**Description**
S	$S_{cur} \cup S_{cand}$
S_i	Set of existing/candidate charging stations within distance d_{th} of user i
y_j	1 if charging station j is built.
$x_{i,j}$	1 if user i will be serviced by charging station j.
Objective 1	Minimize the number of charging stations constructed.
Constraint 2	Every user must be serviced by at least one charging station that is within d_{th} distance of the user.
Constraint 3	User i can use charging station j, only if station j is built.

Algorithm 1: Single Threshold Placement: STP($C, S_{cur}, S_{cand}, d_{th}$)

Input: $C, S_{cur}, S_{cand}, d_{th}$

Construct IP (1–3) from the inputs.

Set $y_j = 1, \forall j \in S_{cur}$.

Solve the IP. Let, S_{new} be the set of newly built stations.

return S_{new}

Before solving this IP, we set $y_j = 1, \forall j \in S_{cur}$. The IP can be solved by existing solvers such as Gurobi [12]. The entire process for solving the special case problem is shown in Algorithm 1, we call this method *Single Threshold Placement* (STP).

Algorithm 2 describes our method *Multi-Threshold Placement* (MTP) for solving Problem 3. The main idea here is that, we go in increasing order of the distance thresholds in D, and cover all the users who can be covered within the current distance threshold. We ensure that at each distance threshold the number of newly built stations is minimized by applying STP (line 5). Note that, stations that are built at threshold d_i are considered as already built when processing the threshold d_{i+1} (line 6). Also, some users in C might not have any location $s \in S_{cur} \cup S_{cand}$ within the largest distance threshold d_k. To cover such users within distance d_k, we consider each of these user locations as candidate locations to build charging stations. We then use STP to determine the minimum number of stations required to cover them with threshold d_k (line 11).

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Algorithm 2: Multi-threshold Placement: MTP$(C, S_{cur}, S_{cand}, D)$

Input: $C, S_{cur}, S_{cand}, D = \{d_1, d_2, ..., d_k\}$
Set of newly built stations: $S_{new} \leftarrow \{\}$
$C_{covered} \leftarrow \{\}$
for $i = 1$ *to* k **do**
  $C_i \leftarrow$ set of users $u \in C$ who have a station $s \in S_{cur} \cup S_{cand}$ within distance d_i.
  $S^i_{new} \leftarrow \text{STP}(C_i, S_{cur}, S_{cand}, d_i)$
  $S_{cur} \leftarrow S_{cur} \cup S^i_{new}$
  $S_{new} \leftarrow S_{new} \cup S^i_{new}$
  $C_{covered} \leftarrow C_{covered} \cup C_i$
$C' \leftarrow C \setminus C_{covered}$
if C' *is not empty* **then**
  $S^c_{new} \leftarrow \text{STP}(C', \{\}, C', d_k)$
return $S_{new} \cup S^c_{new}$

3.2 Connecting EV Charging Stations

The existing power distribution network is a *tree* $\mathcal{G}(\mathcal{V}, \mathcal{E})$ comprising of $N + 1$ nodes (also called *buses*) collected in the set $\mathcal{V} := \{0, 1, 2, \cdots, N\}$. The tree is rooted at substation node $\{0\}$ and consists of primary and secondary distribution lines collected in the edge set $\mathcal{E}$. Secondary distribution lines connect residences to local pole top transformers, which are fed by the distribution substation through the primary distribution lines. We denote the branch bus incidence matrix $\mathbf{E} \in \mathbb{R}^{N\times(N+1)}$ with its element along row l and column k

$$\mathbf{E}(l, k) := \quad 1 \text{ if } k = i, \quad -1 \text{ if } k = j, \quad 0 \text{ otherwise}, \quad \forall l = (i, j) \in \mathcal{E} \qquad (4)$$

We define $\mathbf{E} = \left[\mathbf{e_0}\ \mathbf{E}_{\text{red}}\right]$, where $\mathbf{E}_{\text{red}}$ is the reduced branch bus matrix obtained after removing the column corresponding to the substation (root) node.

In this section, we consider the problem of identifying the optimal connection points for the new EVCSs contained in set $\mathcal{P}$ to the existing distribution network $\mathcal{G}(\mathcal{V}, \mathcal{E})$. Albeit routing power delivery to these new nodes by connecting them to the nearest distribution network node can result in reduced investment for construction, it can lead to power grid reliability issues where node voltages and edge power flows violate prescribed engineering standards. We can formalize this problem as follows.

Problem 4 (Optimal Routing Problem). Given a set of EVCS locations $\mathcal{P}$, find the set of connecting edges $\mathcal{E}_{\text{new}} = \{(p, v)|\ p \in \mathcal{P}, v \in \mathcal{V}\}$ to the existing power distribution network $\mathcal{G}(\mathcal{V}, \mathcal{E})$ such that each new node is connected to exactly one node in the network and the power grid reliability is maintained.

To this end, we start by considering a set of candidate edges for each EVCS location $p \in \mathcal{P}$. In this paper, we consider all nodes $v \in \mathcal{V}$ within ϵ-radius of p and define $\mathcal{E}_D = \{(p, v)\, \forall p \in \mathcal{P} \mid v \in \mathcal{V},\ \text{dist}\,(p, v) \le \epsilon\}$ as the candidate set of

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edges. Then we define a integer optimization program to identify the optimal set of edges $\mathcal{E}_{\text{new}} \subseteq \mathcal{E}_D$ from these candidate edges which minimizes the cost of constructing new distribution line connection to the EVCSs as well as adhere to the power grid reliability standards. Table 2 lists the vectors and matrices used in the optimization problem. A bold character denotes vector/matrix and scalar values are denoted by non-bold subscripted symbols.

Table 2: Vectors and matrices for optimization problem

Var.	Description	Var.	Description
$\mathbf{E}$	branch bus incidence matrix	$\mathbf{E}_{\text{red}}$	reduced branch bus incidence matrix
$\mathbf{p}$	vector of power demand at all nodes	$\mathbf{v}$	vector of node voltage magnitudes
$\mathbf{f}$	vector of power flow through all edges	$\mathbf{c}$	vector of cost of edges
$\mathbf{R}$	diagonal matrix of edge resistances	$\underline{v}, \overline{v}$	lower and upper voltage limits
$\overline{\mathbf{S}}$	diagonal matrix of edge thermal limits		

Node variables. Each node $i \in \mathcal{V} \cup \mathcal{P}$ has associated voltage magnitude v_i which can be stacked into a $(|\mathcal{V}| + |\mathcal{P}|)$-length vector $\mathbf{v}$. Each node in the network has an associated power demand consumption denoted by p_i. The residential load demands are obtained from [30] and the EVCS loads are estimated by considering average number of customers arriving at the location. The power demands can be stacked to vector $\mathbf{p}$.

Edge variables. We define binary variable x_e for each edge $e \in \mathcal{E} \cup \mathcal{E}_D$. $x_e = 1$ denotes that edge e is included in the optimal network, while $x_e = 0$ implies otherwise. Note that $x_e = 1$ for $e \in \mathcal{E}$ since the existing distribution network topology is not altered. We also define f_e to be the power flowing through edge e and cost of each edge to be c_e. The edge variables x_e, f_e and c_e can be respectively stacked to $(|\mathcal{E}| + |\mathcal{E}_D|)$-length vectors $\mathbf{x}$, $\mathbf{f}$ and $\mathbf{c}$.

Radiality constraints. The resulting power distribution network after new edges are added has to maintain a radial or tree structure. This is ensured by ensuring that the number of edges is equal to number of non-root nodes. After the EVCSs in $\mathcal{P}$ are connected, the number of non-root nodes is given by $N + |\mathcal{P}|$. We use the following linear equality constraint: $\sum_{e \in \mathcal{E} \cup \mathcal{E}_D} x_e = N + |\mathcal{P}|$.

Power flow constraints. The power flowing through the edges $\mathbf{f}$ is linearly related to power consumption $\mathbf{p}$ at nodes in the network through the branch bus incidence matrix $\mathbf{E}$. The power flow equations for a network relate node voltages to the power flowing through edges in the network. The standard power flow constraints are quadratic equality constraints which make them non-convex. However, following assumptions of small line impedance values, we arrive at an approximate linear relation between node voltages at edge terminals and power flowing through the edge. This approximation is also known as *Linearized Distribution Flow* (LDF) model [6]. Note that such approximation holds true for edges where $x_e = 1$. Therefore, the LDF model for our case is given as:

$$x_e \left(v_i - v_j - r_e f_e \right) = 0 \quad \forall e := (i, j) \tag{5}$$

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where r_e is resistance of edge e. (5) is non-convex because it has bi-linear terms in the equality. In order to deal with this non-convexity, McCormick relaxation has been used widely in several previous works [28,29]. In general, McCormick relaxation replaces the non-convex equality constraint with its convex envelope [24]. However, in the case of bi-linear variables with at least one binary variable, this relaxation becomes exact. The convex relaxed version of (5) is:

$$-\left(1-x_e\right)M \leq v_i - v_j - r_e f_e \leq \left(1-x_e\right)M \quad \forall e := (i,j) \in \mathcal{E} \cup \mathcal{E}_D \tag{6}$$

Here M is a sufficiently large number such that the inequality turns into a strict equality for $x_e = 1$, while it remains irrelevant when $x_e = 0$. We can construct the diagonal matrix $\mathbf{R}$ with resistance of edges as the entries. An important aspect of the optimization problem is the consideration of power grid reliability constraints. This includes constraints which force node voltages to remain within engineering standards $\underline{v}, \overline{v}$ and edge power flows to be limited by the respective thermal constraints $\overline{s}_e$. We can diagonalize the edge thermal constraints to the diagonal matrix $\overline{\mathbf{S}}$.

The optimization problem aims to minimize overall investment of constructing new power lines required to connect the EVCSs to existing power network. Meanwhile, the voltage at all nodes need to be as close to the rated voltage as possible. This ensures that all consumers have high quality of power delivered to them. In engineering practice, voltage is expressed in per unit (p.u.) which is the ratio of actual voltage to the rated value. Thus, we can minimize the deviation of node voltages to voltage of 1 p.u. We use hyperparameter λ to scale these two separate expressions in the objective function and obtain the following:

$$\min_{\mathbf{x},\mathbf{v},\mathbf{f}} \quad \mathbf{c}^T\mathbf{x} + \lambda||\mathbf{v} - \mathbf{1}||^2 \tag{7a}$$

$$\text{s. to.} \quad \mathbf{E}_{\text{red}}^T\mathbf{f} = -\mathbf{p}, \qquad \overline{\mathbf{S}}\mathbf{x} \geq \mathbf{f} \geq -\overline{\mathbf{S}}\mathbf{x} \tag{7b}$$

$$\left(\mathbf{1}-\mathbf{x}\right)M \geq \mathbf{E}\mathbf{v} - \mathbf{R}\mathbf{f} \geq -\left(\mathbf{1}-\mathbf{x}\right)M, \qquad \underline{v}\mathbf{1} \leq \mathbf{v} \leq \overline{v}\mathbf{1} \tag{7c}$$

$$x_e = 1,\ \forall e \in \mathcal{E};\ x_e \in \{0,1\}\ \forall e \in \mathcal{E}_D, \qquad \mathbf{1}^T\mathbf{x} = N + |\mathcal{P}| \tag{7d}$$

4 Experimental Results

For our experiments, we use the state of Virginia as our study area. To construct a problem instance for this area, we first collected the home locations within the state from a synthetic population data [1], and existing EV charging station locations from US Department of Energy[3]. We also collected locations of 16 different types of POIs (e.g. gas station, train station, airport) from HERE maps [15]. We consider these as candidate locations for building new charging stations. We have collected $\sim$ 3.1 million home locations, 1090 existing EV charging stations, and $\sim$ 1.47 million POIs. Finally, we use the synthetically created power distribution networks [25] for Montgomery County of Virginia, USA to consider the implications on the power grid.

[3] https://afdc.energy.gov/fuels/electricity_locations.html#/analyze?fuel=ELEC

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4.1 EV Charging Station Placement

As mentioned earlier, the number of homes to be covered and the number of candidate locations to build charging stations are quite large. To make the problem more tractable, we do the following: we construct a road network of our study area (using data from HERE maps) and then map each home location, existing EV charging station, and POI to the nearest node in the road network. By doing this, the home locations were mapped to 161,324; the POIs to 25,044; and the existing EV stations to 863 unique nodes. We denote the set of these nodes by C, S_{cand}, S_{cur} respectively. For the set of distance threshold values D, we have chosen $D = \{0.25, 0.5, 2.5\}$ where the unit is miles (experiment with different values of D performed later). C, S_{cand}, S_{cur}, and D together represents our problem instance for Virginia. A visualization of C and S_{cur} is provided in left plot of Figure 1.

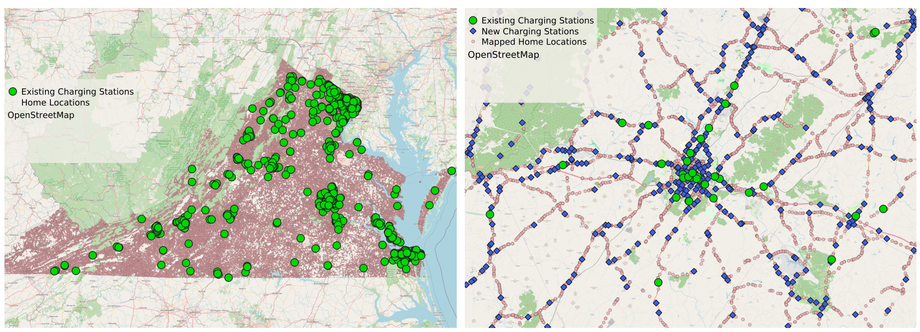

Fig. 1: Plots showing uneven distribution of existing charging stations in Virginia, USA (**left**) and an equitable solution provided by the proposed algorithm for city of Charlottesville (**right**). New stations are built to ensure availability of charging options for all residences.

We applied MTP on our problem instance to find a solution. We ran this experiment on a high-performance computing cluster, with 256GB RAM and 24 CPU cores allocated to our task. MTP terminated with a runtime of $\sim$ 15 minutes. Our solution suggests 10,733 new charging stations needs to be built ($11,596$ stations including the existing ones). Following are some of our observations from this experiment:
(i) Within MTP, STP solves the special case single threshold problem to optimality in every iteration (Algorithm 2 line 5).
(ii) Figure 2 **(left)** shows the distribution of the distances between homes and their nearest charging station, in MTP solution, and when considering only the existing charging stations. Note that, the vertical scale of the two plots are different. With only existing stations, the average distance is 3.64 miles. In MTP solution, 75% of the homes have a charging station within 0.33 miles; the average distance is 0.31 miles.

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(iii) The right plot in Figure 1 shows a visualization of the MTP solution in Charlottesville city, Virginia. We see that new charging stations are built to ensure that homes that are not covered by existing charging stations, are now covered by the new ones.

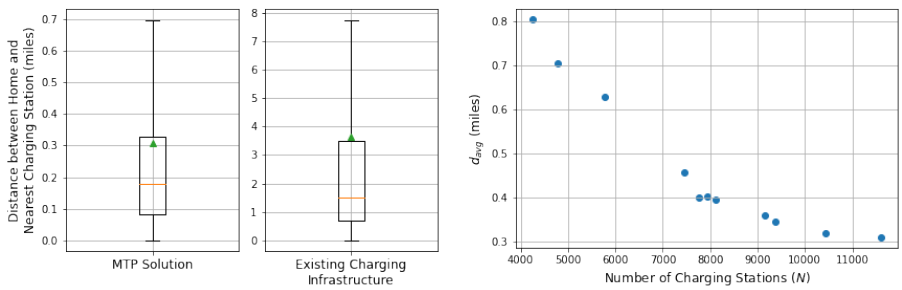

Fig. 2: **(left)** Box-plots showing the distribution of distances between homes and their nearest charging stations, in MTP solution, and when considering only the existing charging stations (scales of the two box-plots are different, outliers are not shown). In MTP solution, 75% of the homes have a charging station within 0.33 miles. **(right)** Scatter plot showing average distance between homes and their nearest charging station (d_{avg}) vs number of charging stations (N). The average distance decreases when we build more stations.

Trade-off between number of charging stations and Average distance between homes and their nearest charging stations In our previous experiment, we have used the distance threshold values $D = \{0.25, 0.5, 2.5\}$ (miles). Intuitively, if we choose smaller threshold values then we will need more charging stations to cover the homes within the smaller distance. On the other hand, if we choose, larger threshold values, then we can cover more homes with fewer number of charging stations. Therefore, we expect a trade-off between the number of charging stations (N) and the average distance between homes and their nearest charging stations (d_{avg}). Now, we investigate this experimentally.

We select 10 different distance threshold sets D. Each set has three threshold values d_1, d_2, d_3, all of which are sampled uniformly at random from the interval $[0.25, 2.5]$. We then solve Problem 3 for our study area with each of these sets, using MTP. This provided us 10 different solutions. Figure 2 **(right)** shows a scatter plot of d_{avg} vs N for each of these solutions. A data point corresponding to our original solution is also shown in the plot (bottom-rightmost data point). We readily see from this scatter plot that there is a trade-off between d_{avg} and N. We can use this plot to choose a suitable solution for our study area. For instance, if there is a budget on the number of stations that can be build, we can filter out the solutions where we go over budget and then choose the solution with the minimum average distance.

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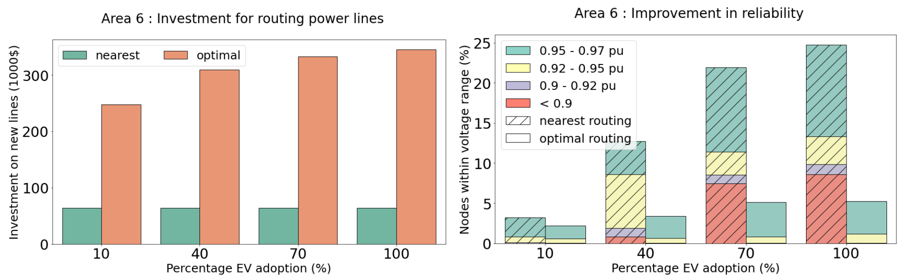

Fig. 3: Plots comparing two different routing algorithms for connecting EV charging stations to existing power distribution network: connecting charging station to the nearest node requires smaller lines as opposed to optimally routing stations. Connecting to nearest available power network node can reduce the additional investment of constructing new power lines (**left**), while it hampers the power grid reliability since we observe multiple undervoltage nodes (**right**) for higher EV adoption rates.

4.2 Optimal Routing Problem

In this section we compare the proposed optimal routing algorithm to the scenario where each EVCS is connected to the nearest available node in the power distribution network. We term this alternate algorithm as the *nearest* routing algorithm. Since EVCSs are connected to the nearest possible node, the new distribution line connections are minimum length edges, which ensures less investment on upgrading existing power infrastructure. However, this comes at a cost of reduced reliability. A *reliable* power grid is considered to be one, which has adequate generation to support the consumer load demand and is operated without violating standard power engineering constraints [5]. In our case, we assume that adequate generation is available to supply the increased demand of EVCSs. We consider the power network to be *reliable* when the line flows (edge flows) are within their rated capacities and the node voltages are within acceptable engineering standards of $0.9 - 1.1$p.u. [3]. Fig. 3 compares the two routing algorithms for different levels of EV adoption. The *nearest* routing algorithm requires minimum investment to be made on installing new lines, while we observe a significant fraction of the nodes in the network having undervoltage issues (less than 0.9 pu) for higher levels of EV adoption. The undervoltage problem disappears when we implement the *optimal* routing algorithm which strictly imposes the voltage limit constraints, but the investment on new line construction increases. We performed our experiments on one of the synthetic networks from Montgomery County in Virginia, USA and identify the region as 'Area 6' in the plots.

The optimal routing algorithm ensures that EVCSs are connected to the power distribution network in a way such that all node voltages are within the accepted engineering standards (greater than 0.9 p.u.). However, this does not ensure that the node voltages are close to the rated voltage (1 p.u.). To this end, we have used the parameter λ in the optimization problem in (7). A higher value

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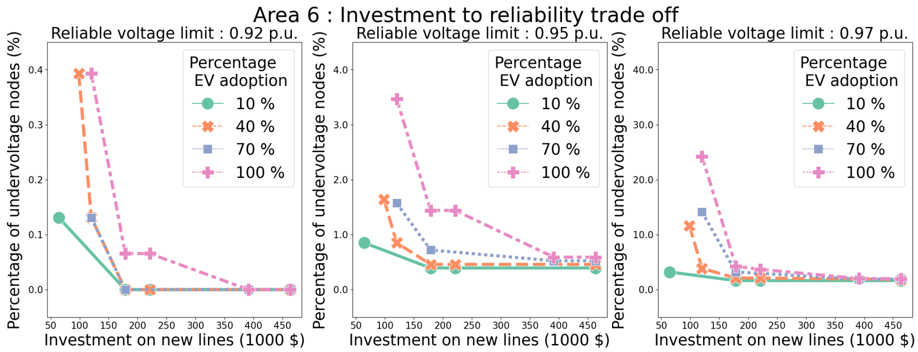

Fig. 4: Plots showing trade off between investment on additional distribution lines and reliability of the power network (vertical scales differ across the three panels). With an increased investment in longer lines, the EVCSs are connected to optimal nodes in the distribution network such that less number of nodes experience undervoltage. For smaller investment, the node voltages are acceptable by standard engineering practices (> 0.9 pu), yet they are far from the rated voltage of 1 pu, making the power grid unreliable.

of λ ensures that the node voltages are closer to rated voltage of 1 p.u. Note that λ has been used as a weight in the objective function – this means that for high values of λ, the aspect of having node voltages closer to the rated voltage is given more importance than minimizing investment on new lines. This trade off is shown in Fig. 4 (vertical scales differ across panels). We plot the investment on new line construction and the number of undervoltage nodes for different values of parameter λ. Since voltages above 0.9 p.u cannot be considered as ‘undervoltage’ as per engineering standards, we define the voltage limits as 0.92 p.u., 0.95 p.u. and 0.97 p.u. for the three plots and consider node voltages less than this limit as ‘undervoltage’.

5 Discussions and Conclusion

Comparison to Related Works: Many current works separately study the optimal placement of EVCS and the effect of EVCS on the power grid. To the best of our knowledge, this work is the first to provide a methodology that combines both into consideration. Individually, our experiment also provides similar findings as some of the previous works.

To build EVCS in order to cover the need of a population, authors in [14] uses the maximum coverage problem (equivalent to our Problem 3 with a single threshold value within D) on the city of Beijing, China. Their paper also includes a similar trade-off between coverage distance and amount of facilities built. The authors also include two other variations on the original problem, one with budgeted constraint and another called p-median. It definitely will be interesting

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to study them with our multi-threshold model; although, due to our large size, certain additional techniques may be needed to make the methodology scalable.

In the context of power reliability, authors in [23] concluded that EVCS that are further away from the power source experiences more fluctuation. This is in line with our finding that spending more budget, often connecting them closer to the substation, increases the overall power grid reliability (Figure 3). Our experiment further shows that not only it reduces the voltage drop of the reconnected nodes, but it also significantly helps other nodes in the network as well. In [32], the authors used simulations to show a drastic increase in power consumption (109%) even at 60% EV penetration. This is consistent with our findings that even at a 40% adoption rate, the number of nodes experiencing undervoltage exceeds double the number observed for 10% adoption rate. Even with optimal connection (Figure 4), across different undervoltage thresholds, similar trends exist where higher adoption with a limiting budget necessarily induces more number of undervoltage nodes (decreased reliability). Although our demand at each charging station is based on the population data and directly correlated with the size and density of the region, unlike [32], we do not propose methods for smoothing the charging demand (e.g. via tariffs). Further studies can be done with these considerations.

Policy Suggestions: By combining real population data and synthetic models of the power grid, we provide a useful analytical tool for policymakers when planning for EVCS. For example, given the chosen threshold of 0.25, 0.5, and 2.5 miles, we see that 10,733 additional EVCS are required. Furthermore, greedily connecting them to the closest point in the existing power grid, even with a 40% adoption rate, imposes a significant decrease in power grid reliability. However, by connecting intelligently, the strain on power grid can be almost entirely eliminated. Policymakers may assess each region independently and decide if optimal connections are warranted. From our experiment, for example, there does not seem to be much difference between the cost in a scenario with 40% adoption versus a 100% adoption, suggesting that if sufficient budget exists, it is worthwhile to prepare for the worst-case scenario.

Future Directions: There are many directions to further extend our model. For example, we may impose limits on how many users may access a particular station due to capacity/space constraints. Our estimation of the demand can also be refined. By using traffic flows or migration data, one may be able to better predict when and where a person will use an EVCS. This time-refined analysis will provide a better estimate of fluctuation since electricity usage varies throughout the day. We can also generalize our optimal connection to allow the rerouting of existing power lines. It is conceivable that altering existing infrastructure might improve the grid reliability regardless of adoption rates.

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