MANAGING VEHICLE CHARGING DURING EMERGENCIES VIA CONSERVATIVE DISTRIBUTION SYSTEM MODELING

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MANAGING VEHICLE CHARGING DURING EMERGENCIES VIA CONSERVATIVE DISTRIBUTION SYSTEM MODELING

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SUMMARY

As the transportation network becomes increasingly electrified, developing evacuation procedures in the case of extreme weather events has emerged as a paramount engineering challenge. In these scenarios, planners are tasked with coordinating electric vehicle charging throughout the evacuating region in a way that minimizes both charging time and electric system overloads. In this thesis, we propose and implement a new, efficient, and flexible mixed-integer linear programming formulation and solution algorithm for this emergency EV charging problem. We accomplish this by leveraging a conservative linear power flow model, a user-selected voltage violation threshold, and a constraint generation algorithm. Furthermore, the proposed methods are evaluated on a test case segment of the larger, urban-suburban distribution network model of the city of Greensboro, NC, under a high EV penetration scenario. These experiments show the successful use of a tractable optimization formulation to minimize of the time required to charge all electric vehicles in urban evacuation at different voltage violation thresholds.

CHAPTER 1
INTRODUCTION

A citywide evacuation scheduling problem aims to mobilize all residents to secure locations in the shortest amount of time before the onset of a natural disaster. This is especially applicable in disasters where the time frame can be well predicted, such as major hurricanes.

While scenarios involving only internal combustion engine (ICE) vehicles focus on modeling the city's transportation network, the dynamics change significantly in cities with a high prevalence of residential EVs [1]. In this context, the transportation and power networks are coupled by the charging requirements of the EVs.

Evacuation planners are then tasked with coordinating not only the departure times and routing of all neighborhoods, but also the charging instructions for all EVs to minimize overloading of the power system. A depiction of the time horizon of the evacuation problem is shown in Figure 1.1, which illustrates both the charging and travel time components of the evacuation horizon.

The evacuation process unfolds across a series of distinct moments. At moment (1), the evacuation commences with the issuance of initial EV charging instructions. Following this, moment (2) signifies the initiation of evacuation proceedings, with detailed routing instructions for each evacuating neighborhood. Moment (3) denotes the conclusion of EV charging across the entire city, while moment (4) designates the scheduled arrival of the last residents at their predetermined safe locations. Notably, moment (4) also marks the onset of the impending natural disaster. During the interval between moments (2) and (3), a unique scenario may arise where some neighborhoods have commenced evacuations while others are still in the process of charging their EVs.

Attempting to minimize the entire timeline illustrated in Figure 1.1 through a single optimization problem presents a formidable challenge. As a result, this study focuses on opti-

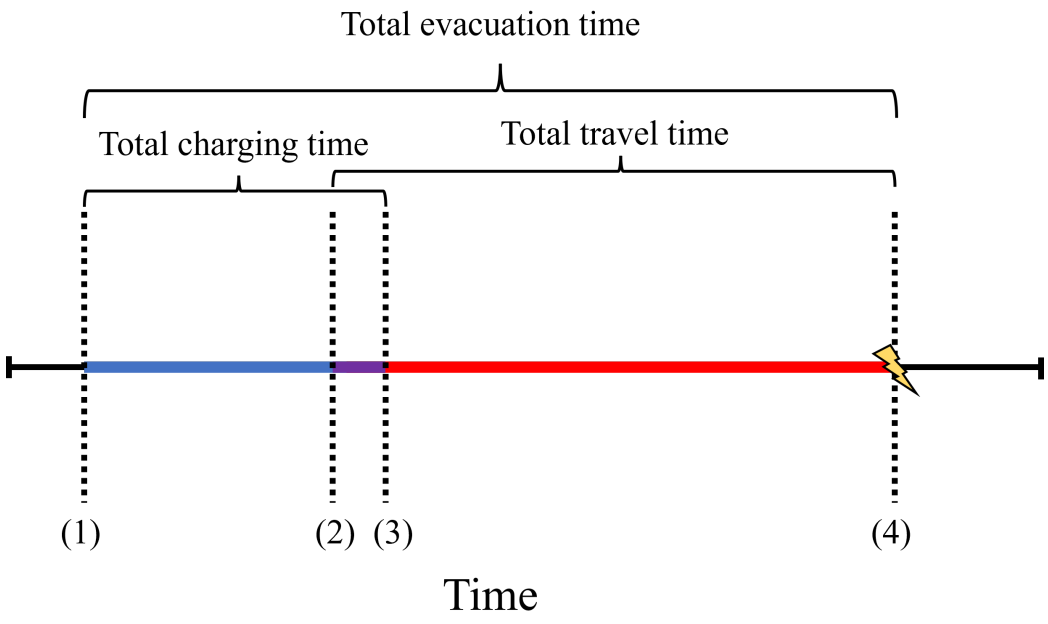

Figure 1.1: High-level illustration of an evacuation plan where charging and travel times are considered. The lightning symbol marks the beginning of a natural disaster.

mizing the interval between moments (1) and (3) in the most effective manner. Developing an efficient formulation for the charging problem stands as a crucial step towards achieving our objective: a systematic iterative process that combines solutions for the charging problem with the results for the departure-schedule-and-routing problem, as outlined in [2] to come up with an optimal and comprehensive evacuation plan.

1.1 Literature review and contributions

Due to the rapid adoption of EVs as an alternative to internal combustion engine (ICE) vehicles, considerable research efforts are being devoted to providing a better understanding of the impacts of EV and to providing better services for all new EV owners. Much of this research is centered around the charging of the EVs, which introduces a new distributed energy resource/flexible load to the electrical network with its own set of opportunities and challenges. Reference [3] presents a conceptual framework to integrating EVs into electric power systems covering the domains of grid operations and electricity markets. Meanwhile, [4] describes the power system level impacts of plug-in hybrid electric vehicles (PHEVs)

focusing on infrastructure loss of life and shift in primary fuel utilization. A survey on the electrification of transportation systems in smart grid environments is provided in [5] showcasing the abundant literature available on topics such as charging facilities and batteries, intelligent energy management, vehicle-to-grid (V2G) technology, and communication requirements for an electrified transportation network.

One particular challenge when it comes to charging large numbers of EVs is that different stakeholders are motivated by a diverse set of objectives. While EV owners seek affordable, readily available electricity and fast charging times, the grid operators must prioritize keeping safe operating parameters, increasing the life span of grid components, and reducing spikes and valleys in electricity consumption. For all of these reasons, multiple charging strategies have been developed. Works such as [6–11] aim to coordinate the charging of EVs to minimize the cost of charging with additional objectives such as shaving peak loads [6, 8, 9], providing frequency and voltage support to the grid [7], and alleviating transformer aging [11]. Others focus on minimizing energy losses [12], proving route mapping alongside charging schedules [13], and preserving the privacy of the users [14]. While some previous research has focused on enabling operators to anticipate grid impacts from the charging of EVs during natural disasters and subsequent evacuations [15, 16], to the best knowledge of the author of this thesis, no article has proposed an algorithm that produces a charging schedule for such an evacuation.

To accomplish the variety of objectives described above, the papers available in the literature use a variety of methodologies including bilevel optimization [6, 10, 11], reinforcement learning [17], bidirectional V2G optimization [7], extended state space modeling [18], hierarchical multi-agent frameworks [8, 9], and co-optimization [12]. These methodologies have been implemented and tested on small synthetic grids such as the IEEE 15-bus case [10] and 33-bus case [6, 7, 13, 14], individual charging stations and parking lots [10, 11], individual neighborhoods [17], and larger city infrastructures [9, 12]. However, none have considered an optimization problem that models a large, unbalanced, three-phase dis-

tribution network. Moreover, since almost none of these works include a transportation network component, the transportation analysis zones (TAZs) are not considered in the charging coordination of EVs.

The contributions of this thesis are threefold. First, we propose a new and efficient mixed-integer linear programming (MILP) formulation and solution algorithm for an emergency EV charging problem using a TAZ framework, and applicable to unbalanced three-phase distribution systems. This formulation enables a user-selected cumulative voltage violation tolerance to address the inherent trade-off between reducing EV charging time and protecting the power system against engineering constraint violations.

Second, we propose and implement the first extension of a data-driven conservative linear power flow model to a large, three-phase distribution network. The power flow model is said to be "conservative" in the sense that the ACOPF constraint set is ensured to be satisfied by the approximated model for the sampled points. This modeling choice greatly improves the tractability of the problem, maintains great prediction accuracy, and places special importance on constraint satisfaction, which is very important for this thesis' application.

Third, we tested the proposed strategies on a segment of the larger, urban-suburban distribution network model of the city of Greensboro, NC, under a high EV penetration scenario. This implementation serves as the first step towards obtaining a full charging schedule for the entire city, and later integrating the charging and routing components of the evacuation scheduling problem as described in the previous subsection.

Future expected contributions are outlined in Chapter 6 along with future research tasks. Current publications resulting from research detailed in this thesis are shown below.

Work from Chapter 2 has been published as:

Gustav Nilsson et al. "GreenEVT: Greensboro Electric Vehicle Testbed". In: *IEEE Systems Journal* 18.1 (2024)

Work from Chapter 3, 4 and 5 are published as:

Alejandro D. Owen Aquino, Samuel Talkington, and Daniel K. Molzahn. "Managing Vehicle Charging During Emergencies via Conservative Distribution System Modeling". In: *2024 IEEE Texas Power and Energy Conference (TPEC)* (2024)

1.2 Organization

The rest of this thesis is organized as follows. Chapter 2 further motivates the need for the emergency EV charging problem. Chapter 3 describes the main challenges of this problem, and the methods we used to circumvent them. Chapter 4 introduces the full optimization problem formulation, as well as the constraint generation algorithm used to solve it. Chapter 5 showcases the experiments and results of applying the proposed methodologies to a relevant test case. Chapter 6 presents some concluding remarks and directions for future research.

CHAPTER 2
MOTIVATION

In the following chapters of this thesis we will formulate and evaluate an optimization problem to minimize the charging time of the EVs in an evacuation area while trying to avoid severe grid overloads. In this chapter, we motivate the need for such optimization problem by showing the effects of a non-optimized charging schedule on the electric grid before an evacuation.

2.1 Evacuation without optimization: Overloads and voltage violations

To underscore the necessity for an optimized EV charging schedule prior to an evacuation, we conducted a series of experiments simulating hypothetical, non-optimized charging scenarios for the city of Greensboro, NC (the same grid infrastructure used for demonstrating the proposed charging optimization problem in the next chapters). For this purpose, we developed the Greensboro Electrical Vehicle Testbed (`GreenEVT`)[1], an integrated platform merging transportation system data with power distribution system data, facilitating power flow simulations under various EV penetration scenarios.

This testbed is built on top of NREL's `SMART-DS` (Synthetic Models for Advanced, Realistic Testing: Distribution systems and Scenarios) [21], which provides realistic-but-not-real distribution network datasets for three regions: industrial, rural, and urban-suburban, and four EV penetration scenarios: low, medium, high, and extreme of the city of Greensboro. In the testbed, we merge the SMART-DS dataset's buses with individual building locations (parcels), and TAZs using public data sources from the state of North Carolina's Guildford County, where Greensboro is located. Furthermore, the distribution system dataset contains sufficient time series load data to create representations of the network for the entire time it takes to charge all EVs before an evacuation.

[1] `GreenEVT` is available at https://github.com/GreenEVT/GreenEVT.

The results from simulating a hypothetical , non-optimized charging schedule are shown in Figure 2.1. This experiment simulates the entirety of the urban-suburban region of the distribution network dataset, comprising 21 substations, 61 feeders, 154,241 buses, and 218,16 total devices. The figure illustrates the progression of overloaded components over a 16-hour charging period for medium, high, and extreme EV penetration projections for the year 2045. In these scenarios, vehicles are assigned random charging start times to mimic a non-optimized charging pattern preceding an evacuation. As anticipated, the number of overloaded components escalates significantly with the increasing number of EVs in the system. Notably, the extreme scenario exhibits 1406% and 401% more overloads than the medium and high scenarios, respectively, across components such as fuses, switches, breakers, lines, and transformers.

Even more significantly, there is a notable surge in undervoltage violations surpassing the acceptable $\pm 5\%$ threshold of nominal voltage range defined in the relevant ANSI standard [22]. Figure 2.2 demonstrates this trend, with the number of undervoltage violations in single phase nodes peaking at 5604, 151514, and 154118 for the medium, high, and extreme scenarios, respectively.

These results serve as a compelling justification for the need to optimize EV charging schedules, especially in the context of impending evacuations. Even when randomly distributing the charging start times over an eight-hour window, these experiments show severe grid overloads and voltage violations, which would only become worse if all EVs were allowed to charge simultaneously. In the next chapters, we propose a methodology to intelligently stagger EV charging start times through an optimization problem and at the same time effectively mitigate the adverse effects shown in this chapter.

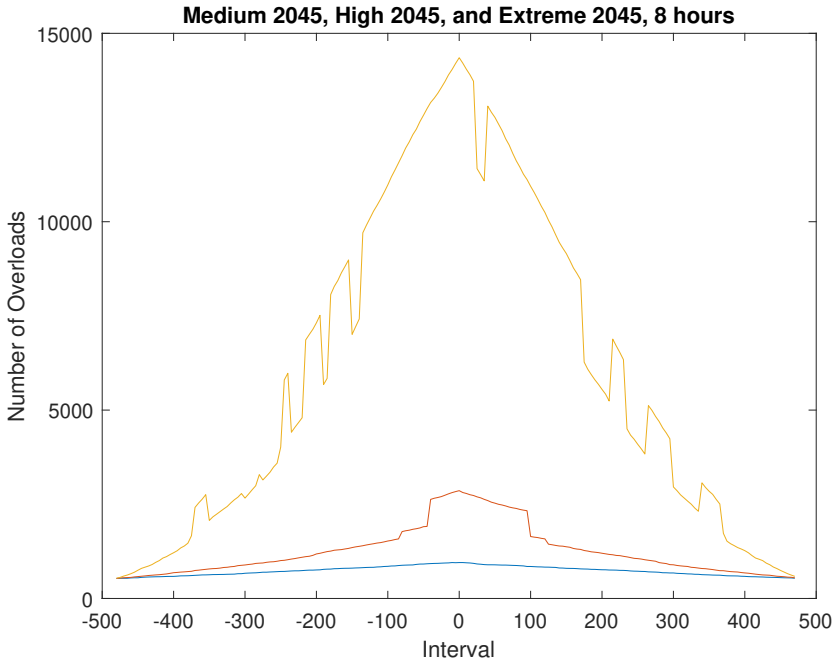

Figure 2.1: Device overloads per interval for Medium 2045 (blue), High 2025 (red), and Extreme 2045 (yellow) EV penetration rates. Vehicle charging start times are randomly assigned over an eight-hour window with each interval representing one minute.

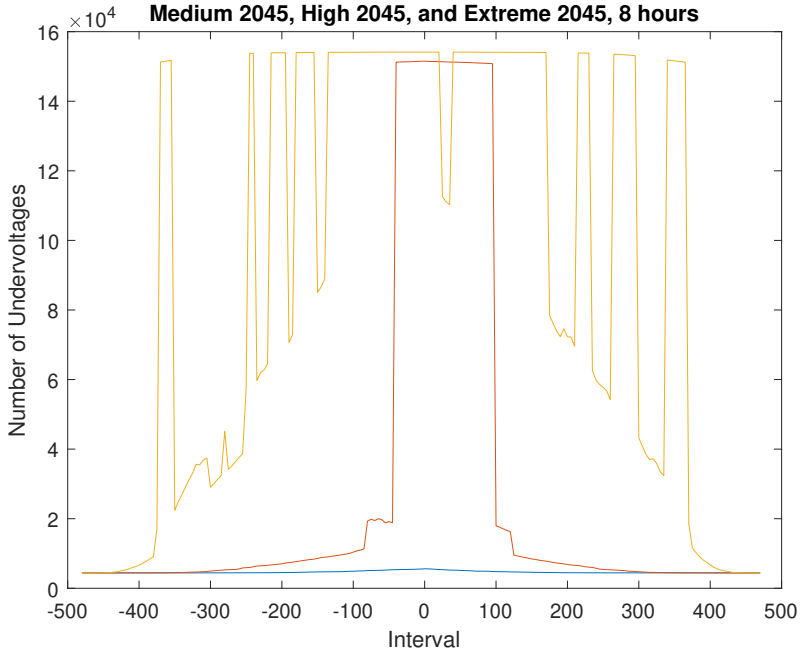

Figure 2.2: Undervoltages (in single-phase nodes) per interval for Medium (blue) 2045, High (red) 2045, and Extreme 2045 (yellow) EV penetration rates. Vehicle charging start times are randomly assigned over an eight-hour window with each interval representing one minute.

CHAPTER 3
CHALLENGES OF THE EMERGENCY ELECTRIC VEHICLE CHARGING (EEV-C) PROBLEM

We formulate and solve an emergency EV charging optimization problem in the aforementioned framework of a disaster evacuation plan. Hereafter, we refer to this problem as the emergency EV charging problem (EEV-C). As in most distribution system optimization problems, the EEV-C problem faces the challenges of modeling vast distribution networks and solving a problem with non-linear, non-convex engineering constraints.

Additionally, solving the EEV-C problem presents a dilemma between (a) a longer charging schedule that avoids network violations and protects grid components from overloading, or (b) allowing violations to expedite EV charging. In the following subsections, we describe these challenges in more detail and propose methods to circumvent them.

3.1 Distribution Network Modeling

Consider a distribution network model represented as a graph $\mathcal{G} = (\mathcal{B}, \mathcal{E})$, where $\mathcal{B}$ and $\mathcal{E}$ represent the set of buses and lines, respectively. The existence of a reference bus is implied. Each bus $j \in \mathcal{B}$ can have up to three phases $\rho \in \mathcal{P}_j \subset \{a, b, c\}$. Each single-phase *node* is denoted as the tuple $i = (j, \rho) \in \mathcal{N}$. The size of $\mathcal{G}$ adds substantial complexity on top of the fact that the power flow equations that govern $\mathcal{G}$ are non-linear and non-convex.

Thus, for the EEV-C problem, we propose modeling the distribution network through the sample-based linearization method first proposed by [23] within the context of transmission networks. This methodology uses constrained regression problems to construct conservative linear approximations (CLAs) of target quantities. The approximations are said to be conservative since they are purposely constructed to either overestimate or underestimate the desired parameters, as exemplified in Figure 3.1. The resulting affine equations can then be used to write upper and lower bounds in optimization problems.

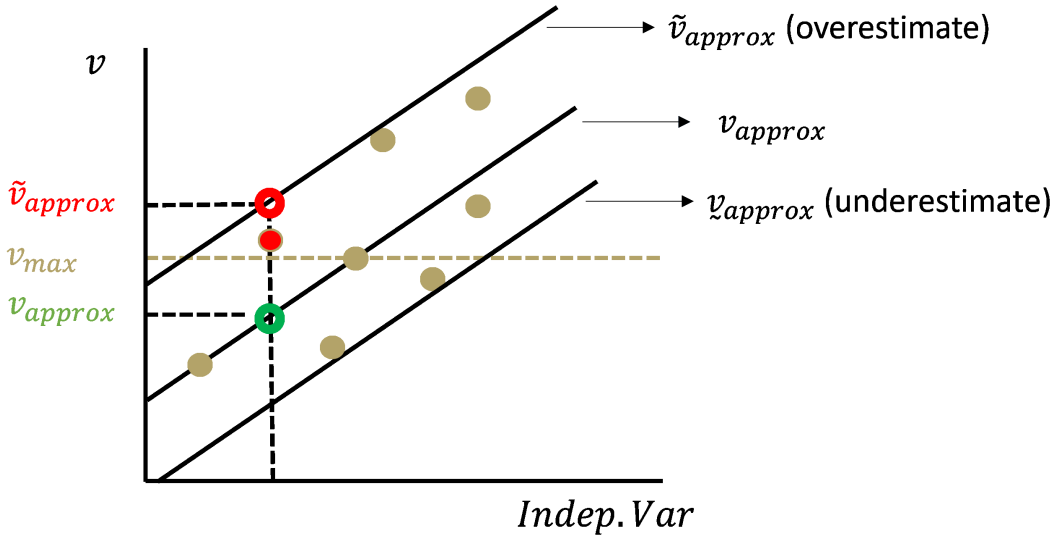

Figure 3.1: Conceptual illustration of the conservativeness of a pair of CLAs (over and underestimates). Using the pair of CLAs (top and bottom lines) would not lead to violations of lower and upper bounds imposed on v as it would when using the non-conservative fit in the middle. In this example, unlike the overestimating CLA, the non-conservative approximation erroneously predicts satisfaction of the upper bound $v_{\max}$ for the red point.

To provide a time-series model of an entire distribution network, we propose constructing the following CLAs:

$$\widetilde{v}_i^t = \widetilde{g}_i(\boldsymbol{p}_{\mathsf{EV}}^t) \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{3.1a}$$

$$\underset{\sim}{v}_i^t = \underset{\sim}{g}_i(\boldsymbol{p}_{\mathsf{EV}}^t) \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{3.1b}$$

where, unlike transmission network CLAs, the approximated quantities $\widetilde{v}_i^t, \underset{\sim}{v}_i^t \in \mathbb{R}$ represent overestimates and underestimates of the squared voltage magnitude of each *single phase node* $i \in \mathcal{N}$ at time steps $t \in \mathcal{T}$. These approximations are defined as affine functions of $\boldsymbol{p}_{\mathsf{EV}}^t$, which denotes the vector of EV active power demands at time t of buses $k \in \mathcal{K} \subset \mathcal{N}$ with designated EVs in them. We symbolize these functions as *overestimating* and *underestimating* CLAs $\widetilde{g}_i^t : \mathbb{R}^{|\mathcal{K}|} \to \mathbb{R}$ and $\underset{\sim}{g}_i^t : \mathbb{R}^{|\mathcal{K}|} \to \mathbb{R}$, respectively. Note that each approximation is time specific, and that the background loads at each time step are treated as constants and *not* input variables to these functions. Rather than voltage magnitudes, we construct approximations of their *squares* to reduce linearization error, as suggested in [23].

Consider the construction of one CLA g_i^t. Let $\boldsymbol{a}_{i,1}^t \in \mathbb{R}^{|\mathcal{K}|}$, and $a_{i,0}^t \in \mathbb{R}$ be coefficients such that g_i^t takes the form of an affine function. Let $\boldsymbol{p}_{\mathsf{EV}}(m) \in \mathbb{R}^{|\mathcal{K}|}$ denote vectors of $m = 1, \ldots, M$ *samples,* where each vector randomizes which EVs are charging in buses $k \in \mathcal{K} \subset \mathcal{N}$. Collect these sample vectors as columns in a sample matrix $\boldsymbol{P}_{\mathsf{EV}} \in \mathbb{R}^{|\mathcal{K}| \times M}$.

Furthermore, let $\boldsymbol{v}_i^t \in \mathbb{R}$ be a vector of computed target measurements of the parameter being approximated by g_i^t. Each entry in this vector is obtained by solving a power flow for each sample vector $\boldsymbol{p}_{\mathsf{EV}}(m)$, and it takes the form

$$\boldsymbol{v}_i^t \triangleq \begin{bmatrix} v_i^t(1) & \ldots & v_i^t(m) & \ldots v_i^t(M) \end{bmatrix}^\top. \tag{3.2}$$

Now we can construct an approximation of a specific squared nodal voltage g_i^t at each time step $t \in \mathcal{T}$ via an ℓ_1-norm approximation program of the form

$$\min_{a_{i,0}^t, \boldsymbol{a}_{i,1}^t} \; ||a_{i,0}^t \mathbb{1} + \boldsymbol{P}_{\mathsf{EV}}^\top \boldsymbol{a}_{i,1}^t - \boldsymbol{v}_i^t||_1 \tag{3.3a}$$

$$\text{s.t} \quad a_{i,0}^t \mathbb{1} + \boldsymbol{P}_{\mathsf{EV}}^\top \boldsymbol{a}_{i,1}^t \leq \boldsymbol{v}_i^t \quad \text{if underestimate} \tag{3.3b}$$

$$a_{i,0}^t \mathbb{1} + \boldsymbol{P}_{\mathsf{EV}}^\top \boldsymbol{a}_{i,1}^t \geq \boldsymbol{v}_i^t \quad \text{if overestimate,} \tag{3.3c}$$

where $(\cdot)^\top$ denotes the transpose of a matrix, and $\mathbb{1}$ symbolizes a vector of all ones.

If building an overestimate (resp. underestimate), constraints (Equation 3.3c) (resp. (Equation 3.3b)) are included to ensure that all predictions made by the resulting CLA are above (resp. below) the sampled measurements. The ℓ_1-norm objective can be motivated by empirical indications that the coefficients corresponding to linear approximations of distribution network models are often sparse. The program (Equation 3.3) is a linear program with affine inequality constraints, which can be easily solved.

Lastly, a time-varying distribution network model can be formulated within optimization problems using the previously computed CLAs via the following upper and lower bounds:

$$\widetilde{g}_i^t(\boldsymbol{p}_{\mathsf{EV}}^t) \leq \overline{v_i} \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{3.4a}$$

$$\underset{\sim}{g}_i^t(\boldsymbol{p}_{\mathsf{EV}}^t) \geq \underline{v_i} \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{3.4b}$$

where $\overline{v_i}$ and $\underline{v_i}$ represent the maximum and minimum squared voltage magnitudes at node i, respectively.

In the coming sections, we explain the need for *conservative* approximations to generate stronger constraints than that of simple linear regression, as in (Equation 3.4). We also explain how to solve the EEV-C problem while only explicitly enforcing a subset of these constraints.

3.2 Trade-off between charging time and constraint violations

Another challenge of the EEV-C problem is the inherent trade-off between the objective of minimizing total EV charging time and the desire to protect the power system from dangerous constraint violations. In Chapter 2 we show that given current distribution grid infrastructures, the number of network violations increases greatly as one increases the number of EVs charging simultaneously. Since the optimization algorithm will naturally try to charge as many EVs simultaneously, grid constraints may render infeasible some of the most desirable solutions, thereby delaying the evacuation process.

In addition, due to the urgency of an emergency evacuation, grid operators may want to allow the network to operate above its normal limits. To model this choice, we introduce the non-negative slack variables $\lambda_i^{t,+}$ and $\lambda_i^{t,-}$ for the upper and lower bounds in (Equation 3.4), respectively. Additionally, we add a new constraint (Equation 3.5c) to the CLA distribution network model, which upper bounds the sum of all the slack variables. The upper bound Λ_{max} allows the operator to pick a tolerable cumulative violation amount across the entire network. The CLA distribution model with allowable violations is then:

$$\widetilde{g}_i^t(\boldsymbol{p}_{\mathsf{EV}}^t) \leq \overline{v_i} + \lambda_i^{t,+} \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{3.5a}$$

$$\underset{\sim}{g}_i^t(\boldsymbol{p}_{\mathsf{EV}}^t) \geq \underline{v_i} - \lambda_i^{t,-} \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T} \tag{3.5b}$$

$$\sum_{i \in \mathcal{N}} \sum_{t \in \mathcal{T}} (\lambda_i^{t,+} + \lambda_i^{t,-}) \leq \Lambda_{\mathsf{max}} \tag{3.5c}$$

$$\lambda_i^{t,+}, \lambda_i^{t,-} \geq 0 \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T}. \tag{3.5d}$$

CHAPTER 4
ITERATIVE EEV-C PROBLEM USING CONSERVATIVE LINEAR APPROXIMATIONS (CLA-EEV-C)

We formulate the EEV-C problem using the surrogate distribution network model described in section 3.1. This grants the grid operator the flexibility to select a tolerable threshold of network violations throughout the system. Additionally, we introduce an iterative constraint generation algorithm designed to enhance tractability when solving the problem.

4.1 Formulation

We first state the modeling assumptions that are used for the reminder of this work.

- *Assumption 1:* The background loads (without any EV charging) follow the patterns of a typical mid-summer day.
- *Assumption 2:* EV loads operate at unity power factor, and their charge rate is 7.5 kW. It takes 32 time periods (8 hrs) to charge an EV from 0% to 100% at this rate.
- *Assumption 3:* When a TAZ is given the order to start charging, its EVs must charge until they reach full capacity. An EV may only charge after its TAZ was given the order to start charging.
- *Assumption 4:* There are no more than 96 time periods (24 hrs) available to charge all EVs.
- *Assumption 5:* The starting battery level of all EVs is treated as an input (known) parameter.

The objective of the EEV-C problem is to minimize the number of time periods, each of 15 minutes, that it takes to charge all EVs in a region while satisfying an upper bound on the magnitude of grid violations imposed by the grid operator. As a result, the algorithm pushes

the charging of all vehicles as close as possible to their evacuation departure deadlines, thereby minimizing the amount of preparation time needed ahead of an incoming disaster. The proposed model uses a well-studied framework for evacuation that partitions a city into Transportation Analysis Zones (TAZs). As evacuation instructions are given at the TAZ level (rather than feeder, street, or neighborhood levels), they are both realistic and computationally meaningful [24, 25]. Concretely, we denote the set of all TAZs as Ξ, where every $\xi \in \Xi$ is an individual TAZ with multiple EVs registered in it. Let $E_\xi = \{1, \ldots, |E_\xi|\}$ be the set of electric vehicles registered within TAZ ξ, and $\mathcal{K}$ denote the set of buses $k \in \mathcal{K} \subset \mathcal{B}$ with EVs in them.

Altogether, the EEV-C problem is presented in (Equation 4.1). We denote $\Gamma_{\mathsf{max}} \in \mathbb{R}$ as the time step when the first TAZ starts charging. The objective function (Equation 4.1a) maximizes Γ_{max} to make it as close as possible to the first moment of the evacuation. This is defined implicitly via (Equation 4.1b) using $\tau^t \in \{0, 1\}$, where $\tau^t = 1$ if some TAZ has started charging prior to t and 0 otherwise.

$$\max_{\boldsymbol{\tau}, \boldsymbol{C}_{\xi,h}, \boldsymbol{C}_\xi} \quad \Gamma_{\mathsf{max}}, \quad \text{subject to:} \tag{4.1a}$$

$$\Gamma_{\mathsf{max}} \leq t\tau^t + T(1 - \tau^t) \quad \forall t \in \mathcal{T} \tag{4.1b}$$

$$\tau^t \geq \frac{\sum_{\xi \in \Xi} \sum_{t'=1}^{t} C_\xi^{t'}}{T|\Xi|} \quad \forall t \in \mathcal{T} \tag{4.1c}$$

$$L_{\xi,h}^t = L_{\xi,h}^{t-1} + \frac{1}{\beta} C_{\xi,h}^{t-1} \quad \forall t \in \mathcal{T}, \forall \xi \in \Xi, \forall h \in E_\xi \tag{4.1d}$$

$$L_{\xi,h}^0 \leq L_{\xi,h}^t \leq 1 \quad \forall t \in \mathcal{T}, \forall \xi \in \Xi, \forall h \in E_\xi \tag{4.1e}$$

$$C_\xi^t \geq C_\xi^{t-1} - \frac{\sum_{h \in E_\xi} L_{\xi,h}^t}{|E_\xi|} \quad \forall t \in \mathcal{T}, \forall \xi \in \Xi \tag{4.1f}$$

$$C_\xi^t \leq 2 - \frac{1 + \beta \sum_{h \in E_\xi} L_{\xi,h}^t}{\beta |E_\xi|} \quad \forall t \in \mathcal{T}, \forall \xi \in \Xi \tag{4.1g}$$

$$C_\xi^t - L_{\xi,h}^t \leq C_{\xi,h}^t \leq C_\xi^t \quad \forall t \in \mathcal{T}, \forall \xi \in \Xi, \forall h \in E_\xi \tag{4.1h}$$

$$\frac{\sum_{h \in E_\xi} L_{\xi,h}^{d_\xi}}{|E_\xi|} = 1 \quad \forall \xi \in \Xi \tag{4.1i}$$

$$p^t_{EV_k} = \sum_{(\xi,h)\in\Upsilon_k} C^t_{\xi,h} R \quad \forall t \in \mathcal{T} \tag{4.1j}$$

(Equation 3.5a)–(Equation 3.5d)

$$\tau^t, C^t_\xi, C^t_{\xi,h} \in \{0,1\} \quad \forall t \in \mathcal{T}, \forall \xi \in \Xi, \forall h \in E_\xi. \tag{4.1k}$$

The main decision of interest in this program is *when* each of the TAZs start charging. Once a TAZ $\xi \in \Xi$ starts charging, *all* EVs $h \in E_\xi$ in that TAZ will charge until they reach full capacity. The charging progression of each EV is modeled by equations (Equation 4.1d)–(Equation 4.1e), where each EV $h \in E_\xi$ has an initial state of charge of $L^0_{\xi,h}$ and a battery level $L^t_{\xi,h}$ at time period $t \in \mathcal{T}$. Additionally, β denotes the number of time steps it takes to fully charge an EV from 0% at rate R, and each $\xi \in \Xi$ is assigned a binary variable $C^t_\xi \in \{0,1\}$, which takes the value of 1 if TAZ ξ is charging at time t, and 0 otherwise. After all EVs in a TAZ are at full capacity, the entire TAZ will stop charging. This behavior is modeled by constraints (Equation 4.1f)–(Equation 4.1g), where the binary variables $C^t_{\xi,h} \in \{0,1\}$ take the value of 1 if vehicle h in TAZ ξ is charging at time t, and 0 otherwise. Furthermore, constraint (Equation 4.1h) ensures that an EV can only charge if its TAZ is instructed to charge.

Constraint (Equation 4.1i) ensures that each EV in a TAZ is fully charged by its TAZ departure time period d_ξ. Constraint (Equation 4.1j) links the EV demand across time to their charging schedules, where Υ_k denotes the set of individual EVs (ξ, h) that are assigned to bus k . Constraints (Equation 3.5a)–(Equation 3.5d) represent the *surrogate* network model, and its linearized network constraints described in section 3.1. Since the surrogate network constraints (as well as all other constraints related to the charging of EVs) are linear, we have a mixed-integer linear program (MILP).

4.2 Solution Algorithm

Applying the constraints (Equation 3.5a)–(Equation 3.5b) to the EEV-C problem admits the advantage of simplicity relative to the AC OPF constraints. Nonetheless, the large number

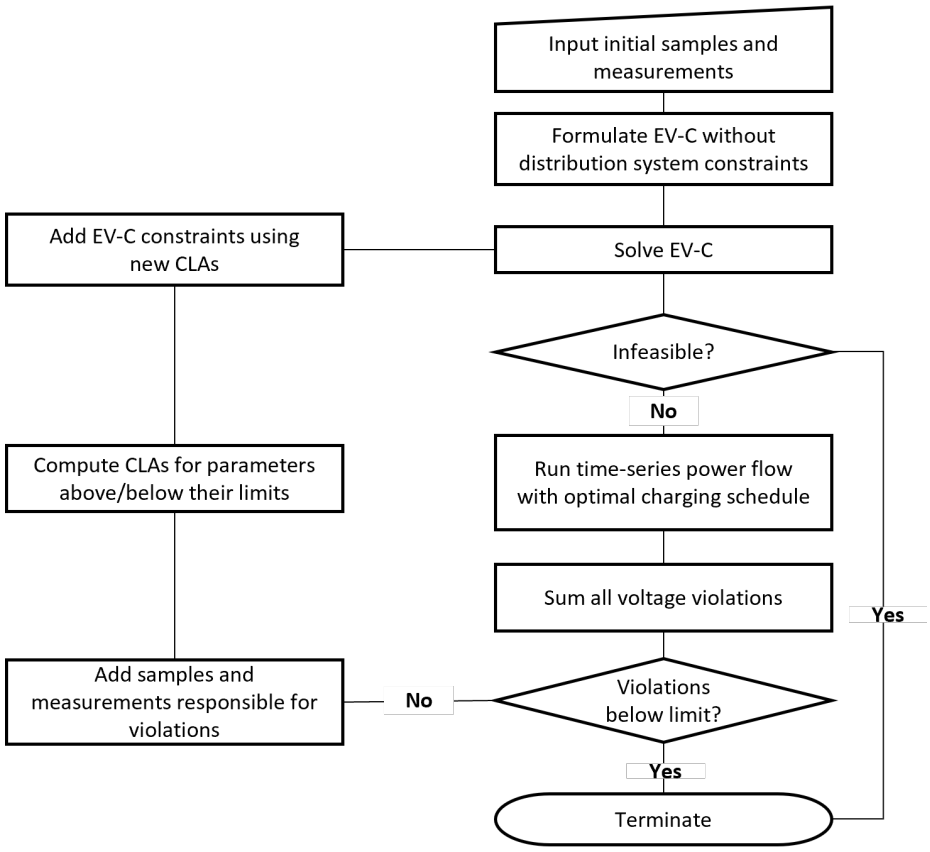

Figure 4.1: Flowchart of the constraint generation algorithm in the EEV-C problem.

of constraints can still render an intractable model, particularly for large networks. Furthermore, even when taking advantage of parallel computing, generating all of these CLAs would require significant up front computational effort. For these reasons, we propose solving (Equation 4.1) using the iterative constraint generation scheme outlined in Figure 4.1.

The algorithm begins by processing an initial matrix $\boldsymbol{P}_{\mathsf{EV}}$ and vectors $\boldsymbol{v}_i^t$ for all $(i,t) \in \mathcal{N} \times \mathcal{T}$. Initially, it solves the EEV-C problem (Equation 4.1) without voltage constraints (Equation 3.5a)-(Equation 3.5b), generating a "naive" charging schedule that disregards potential power system violations. Subsequent time-series power flow analysis on this schedule identifies any actual voltage violations. If these exceed the grid operator's allowable limit Λ_{max}, the algorithm iteratively adds distribution system constraints until the violation limit is met or infeasibility is proven.

New constraints are formed by constructing CLAs through constrained regression problems like (Equation 3.3). These constraints are based on parameters that violated limits in the previous iteration's charging schedule, as assessed by a power flow solver. With each iteration, measurements of these violated parameters and the corresponding EV active power demands $\boldsymbol{p}_{\mathsf{EV}}^{t}$ are added to the sets of measurements and samples.

Using conservative approximations significantly speeds up the convergence of the iterative approach. Since the conservative constraints are stronger than those created from simple least-squares regression, they exert greater influence on forcing new solutions to the EEV-C problem at each iteration. This, in turn, accelerates the algorithm's convergence, leading to fewer iterations and reduced computation time.

CHAPTER 5
NUMERICAL EXPERIMENTS AND DISCUSSION

We numerically validate the proposed methods on a synthetic model of the distribution network of the city of Greensboro, NC. To achieve this, we make use of the Greensboro Electrical Vehicle Testbed, which provides a precise coupling of each bus in the power network to its corresponding transportation analysis zone (TAZ) in the transportation system.

In this test case, we will simulate the high EV penetration scenario for substation 19 in the urban-suburban region, which contains 3 feeders and a total of 4815 single phase nodes. All optimization problems, including the EEV-C problem and the constrained regression problems used to compute CLAs, were solved using Gurobi v10.0.1. Additionally, all the power flow solutions were computed using the power flow simulator `OpenDSS` [26] and the Python interface `yadi` [27]. The computations were carried out on Georgia Tech's PACE cluster using a computing node equipped with a quad-core 2.7 GHz processor and 64 GB of RAM.

5.1 Total charging time vs Allowable violations

Solving the EEV-C problem across multiple values for Λ_{max} reveals the trade-off between total charging time and network violations, shown in the top of Figure 5.2. As expected, an increase in permissible violations correlates with a reduction in the time required to charge the EVs in all three TAZs within this specific test case. Note that significant reductions in charging time occur primarily at the lower and upper ends of this curve, featuring a 9.09% decrease when increasing Λ_{max} from 0 to 0.4, and a substantial 45.76% decrease when increasing Λ_{max} from 2.5 to 2.87. Note that raising Λ_{max} to 2.87 mirrors the absence of constraints on the distribution network, resulting in the "naive" charging schedule.

The lower section of Figure 5.2 uses Gantt charts to provide a visual representation of the optimal charging schedules obtained under different values of Λ_{max}. In these charts,

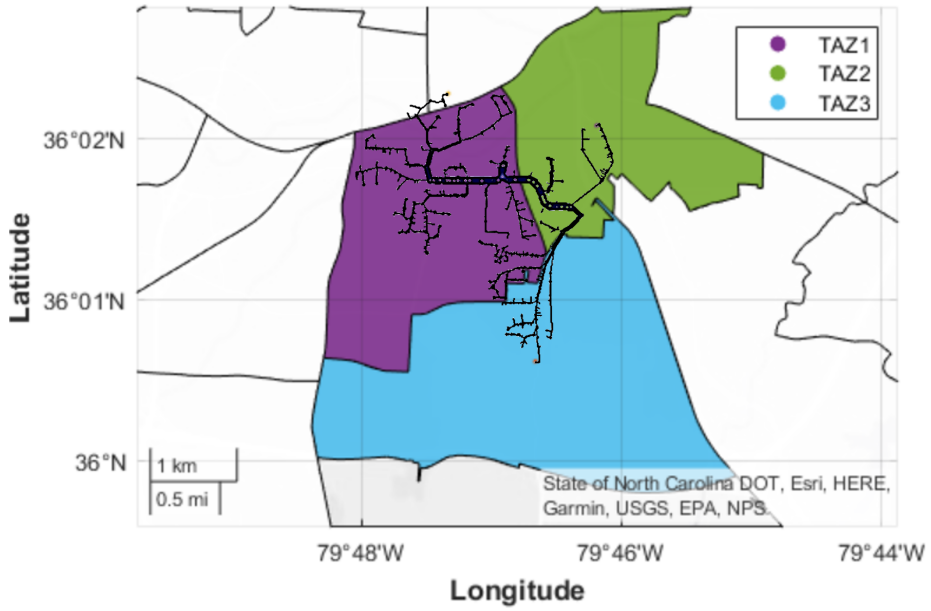

Figure 5.1: Geographic map of the distribution network downstream of substation 19 in Greensboro's urban-suburban network. TAZ1, TAZ2, and TAZ3, which surround this network, are shown in blue, red, and yellow, respectively.

each horizontal bar depicts the time intervals for charging each TAZ whose vehicles are all scheduled to depart at $t = 96$. Interestingly, when $\Lambda_{\max} = 0$, a 2.75 hour gap appears between time steps 52 and 63, during which no vehicles are actively charging. This behavior suggests that the background loads at these time steps are causing considerable delays in the charging of TAZ1 and TAZ2, thereby emphasizing the potential advantages of implementing demand response strategies in emergency scenarios of this nature.

5.2 Analysis of the iterative algorithm

Each data point in the upper graph of Figure 5.2 is obtained using the iterative algorithm detailed in Section section 4.2. For this specific test case, all data points converged within an average time of 4.01 hours, and in between 1 and 4 iterations Additionally, these points converged with an average relative error of 0.68% between predicted and actual cumulative violation magnitudes in the last iteration. This result points to the strong predictive performance of the proposed CLA distribution network model, particularly in the last iterations of the algorithm, where a larger set of CLAs constraints are used to describe the network.

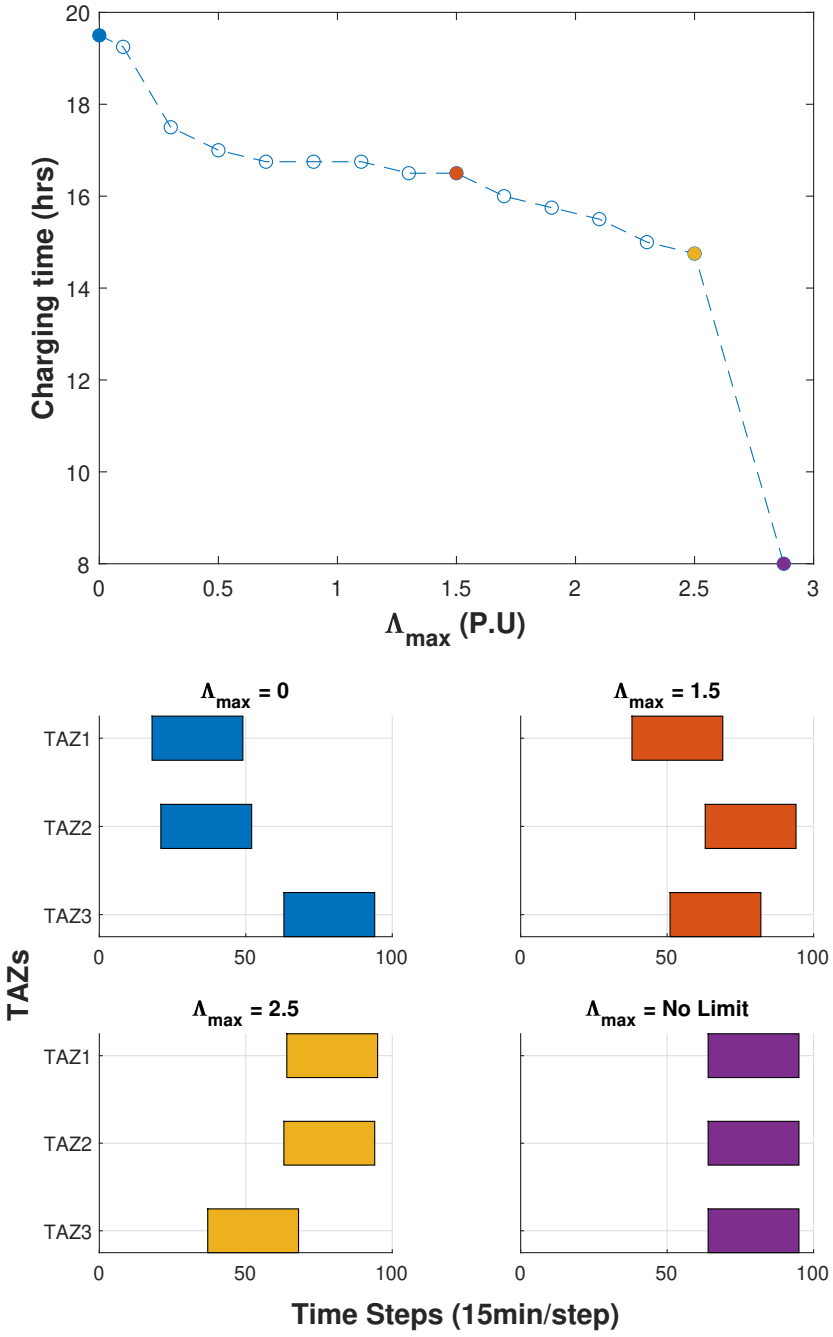

Figure 5.2: The top graph shows the optimal charging time at varying allowable violation thresholds. The bottom four graphs show the charging schedules that achieve the optimal charging times at specific points in the top graph.

The iterative process of obtaining the EEV-C solution when $\Lambda_{\mathsf{max}} = 0$, $\Lambda_{\mathsf{max}} = 1.5$, and $\Lambda_{\mathsf{max}} = 2.5$ is shown in the top graph of Figure 5.3. Each of these three runs converged when the sum of actual violations in the optimal charging schedule (produced when solving the EEV-C problem) reached their respective thresholds of Λ_{max}. Since the solution algorithm always starts by solving the problem without any grid constraints, all three curves share a common starting point at the first iteration. Subsequent iterations reveal how the algorithm's approach does not always result in an immediate reduction of actual violations, but successfully reaches convergence within a few iterations.

The proposed solution algorithm and EEV-C formulation produces monotonically decreasing charging times over Λ_{max}, as anticipated. However, note that it does not produce a monotonically increasing sum of violation magnitudes nor violation counts, as one would expect. This behavior is prominently depicted in the bottom graph of Figure 5.3, where an increase in Λ_{max} from 0.7 to 0.9 results in a *decrease* in both the total violation count and the cumulative violation magnitudes. This observation indicates that once the algorithm identifies an optimal charging schedule for a particular Λ_{max}, it does not continue to explore solutions that maintain the same charging time while further reducing network violations.

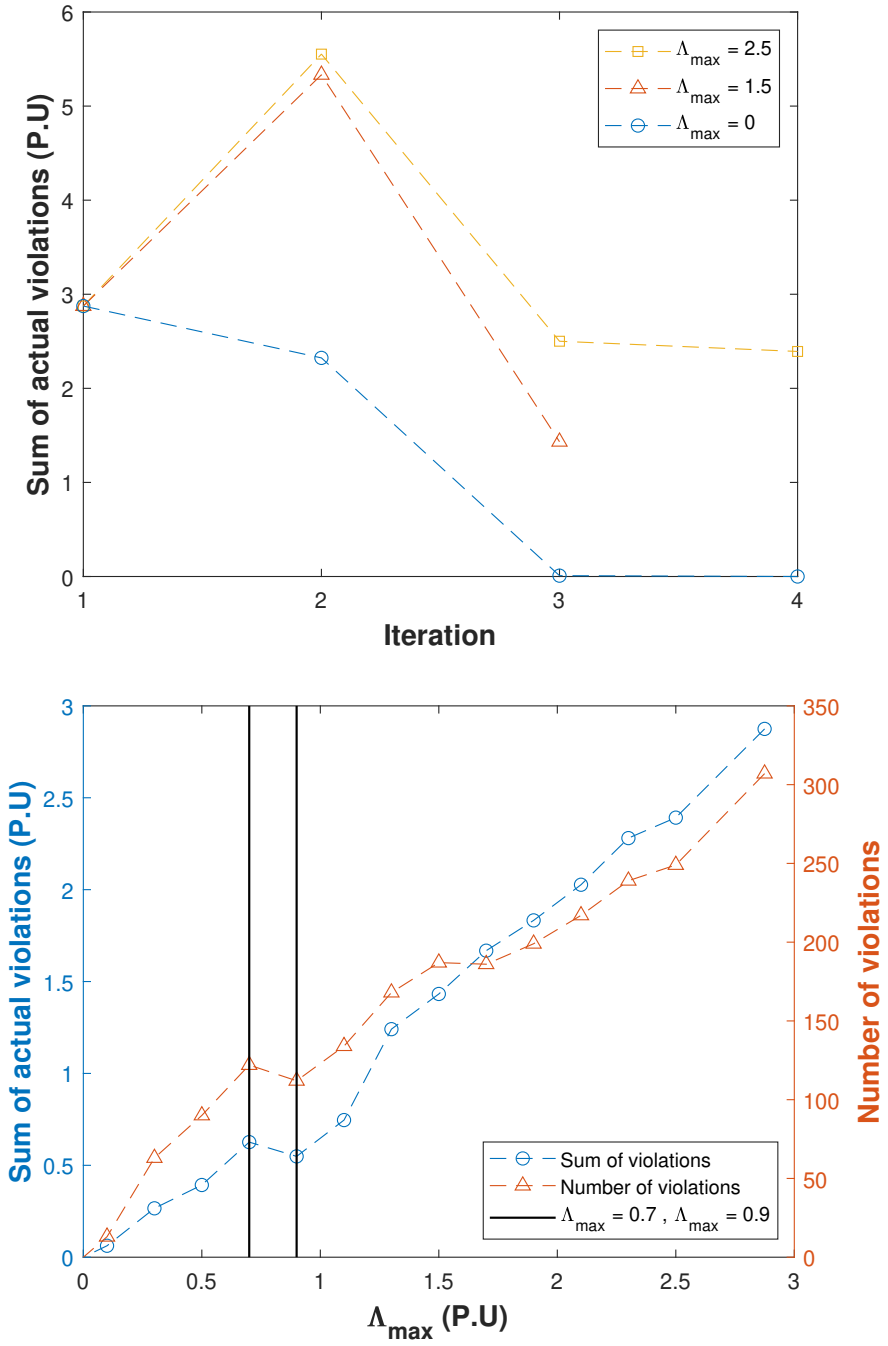

Figure 5.3: The top graph shows the trajectory of the sum of actual violations during the iterative algorithm for three different values of Λ_{max}. The bottom graph shows the sum of violation magnitudes and the number of violations vs. Λ_{max} using the left and right y-axes, respectively. The two vertical lines at $\Lambda_{max} = 0.7$ and $\Lambda_{max} = 0.9$ highlight the non-monotonic nature of both curves.

CHAPTER 6
CONCLUSIONS AND FUTURE RESEARCH

In this work, we proposed an emergency EV charging scheduling formulation that leverages an embedded distribution network model featuring conservative power flow linearizations. The formulation provides flexibility by enabling the user to define an acceptable constraint violation threshold, and strike a balance between minimizing total EV charging time and safeguarding the power system from potential hazards. To tackle the computational complexity of the problem, we also presented an algorithm that explicitly enforces only a subset of the linearized power grid constraints at each iteration, thereby contributing to a more manageable solution approach.

The proposed methodology was tested on a small region of a larger distribution network model of the city of Greensboro, NC, under a high EV penetration scenario. The results demonstrate the effectiveness and accuracy of the linearized distribution model used in the formulation, and provide an illustration of the marginal utility of allowing different degrees of cumulative voltage violations in order to reduce the EV charging timeline. However, the experiments reveal that while the solution algorithm successfully minimizes total EV charging time within the defined violation threshold, it falls short of simultaneously minimizing violations while maintaining the optimal charging time.

These results motivate several avenues for future research, including:

1. Extending the proposed formulation to co-minimize charging times and network violations.

2. Exploring decomposition techniques to scale the formulation for the entire city of Greensboro, including its 21 substations and over 60 TAZs.

3. Incorporating line and transformer current CLAs into the distribution network model and assessing the tractability of the resulting formulations.

4. Finally, integrating these outcomes into a broader citywide evacuation plan that includes a departure-scheduling-and-routing problem.

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