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Deanship of Graduate and Professional Studies

Optimal Scheduling of Electric Vehicle Charging Loads in Distribution Networks Using Model Predictive Control

A Thesis Presented to
the Deanship of Graduate and Professional Studies
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for the Degree of

Master of Science in Electrical Engineering

By

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Dedication

To my parents, whose sacrifices made this work possible, and to my wife, whose patience and encouragement carried me through every long night in the lab.

Acknowledgment

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Abstract

Full Name: Faisal Al-Otaibi
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The rapid adoption of electric vehicles (EVs) in urban distribution networks introduces significant uncoordinated charging loads that can cause transformer overloading, voltage excursions, and increased peak demand. This thesis develops a model predictive control (MPC) framework for coordinated scheduling of residential and workplace EV charging loads at the feeder level. The proposed controller formulates a receding-horizon optimization problem that minimizes a weighted combination of transformer loss-of-life, voltage deviation, and total energy cost, subject to charger power limits, state-of-charge targets, and network operating constraints. A reduced-order distribution feeder model calibrated against a 400-node test network is used to evaluate controller performance under three charging-demand scenarios representative of the Dhahran residential grid. Simulation results, benchmarked against uncoordinated and rule-based charging baselines, show that the MPC scheme reduces peak transformer loading by 27.4%, improves worst-case bus voltage deviation by 41.8%, and lowers aggregate energy cost by 12.6%, while meeting 98.7% of driver departure state-of-charge requirements. Sensitivity analysis further indicates that the controller remains robust to forecast errors of up to 15% in aggregate charging demand. The results suggest that feeder-level MPC scheduling is a practical and scalable alternative to costly infrastructure upgrades for accommodating growing EV penetration in constrained distribution networks.

Chapter 1

Introduction

1.1 Background and Motivation

The Kingdom's National Transport Strategy targets significant electric vehicle (EV) market penetration by 2035, a shift that will place unprecedented stress on distribution feeders originally sized for conventional residential and commercial loads. Unlike traditional appliances, EV chargers draw sustained power over multi-hour windows and, when uncoordinated, tend to cluster around evening arrival times – precisely when feeders are already near peak loading. Left unmanaged, this coincidence can accelerate transformer aging, cause under-voltage conditions at the ends of long feeders, and force costly, reactive infrastructure upgrades.

Key challenge. Distribution utilities must accommodate rapidly growing EV charging demand without proportional investment in feeder and transformer capacity, motivating software-based load coordination as a near-term mitigation strategy.

Model predictive control (MPC) is a natural candidate for this coordination problem: it explicitly handles constraints, incorporates forecasts of driver behavior and electricity price, and re-optimizes at each control step to correct for prediction error. This thesis investigates whether a feeder-level MPC scheduler can deliver measurable reductions in peak loading and voltage stress while preserving an acceptable quality of service for EV drivers.

1.2 Problem Statement

Given a distribution feeder serving N EV chargers with stochastic driver arrival and departure times, the scheduling problem is to determine, at each control interval, the charging power set-point for every connected vehicle such that:

1. transformer and conductor thermal limits are respected at all times,

2. bus voltages remain within the ±5% statutory band,
3. each vehicle reaches its driver-specified departure state-of-charge (SoC) target, and
4. total energy procurement cost is minimized under time-of-use tariffs.

1.3 Research Objectives

1. Formulate a receding-horizon MPC problem for coordinated EV charging at feeder scale.
2. Develop a reduced-order feeder model suitable for real-time optimization.
3. Benchmark the proposed controller against uncoordinated and rule-based baselines.
4. Evaluate robustness to demand-forecast uncertainty through sensitivity analysis.

1.4 Thesis Organization

Chapter 2 reviews prior work on EV charging coordination and MPC applications in distribution systems. Chapter 3 presents the feeder model, MPC formulation, and solution methodology. Chapter 4 reports simulation results and comparative evaluation. Chapter 5 concludes with a summary of contributions, limitations, and directions for future work.

Chapter 2

Literature Review

2.1 Uncoordinated and Rule-Based Charging

Early studies of EV integration assumed uncoordinated, arrival-triggered charging and quantified its impact on transformer loading and feeder losses. Subsequent work introduced simple rule-based mitigations, such as staggered start times or price-triggered delays, which reduce peak coincidence but do not explicitly account for network constraints or optimize a cost objective.

2.2 Optimization-Based Scheduling

A substantial body of work formulates EV scheduling as a centralized optimization problem, typically minimizing energy cost or peak demand subject to charger and network constraints. Mixed-integer linear programming and convex relaxations of the AC power flow equations have both been applied, with the latter offering tractability at the expense of some model fidelity. Table 2.1 summarizes representative approaches.

Table 2.1: Summary of representative EV scheduling approaches

Approach	Objective	Network Model	Horizon
Rule-based staggering	Peak reduction	None	Reactive
Centralized LP	Cost minimization	Copper-plate	Day-ahead
Convex OPF relaxation	Cost + voltage	Linearized	Day-ahead
Distributed ADMM	Cost + fairness	Radial approx.	Day-ahead
Receding-horizon MPC	Cost + voltage + thermal	Reduced-order	Real-time

2.3 Model Predictive Control for Distribution Systems

MPC has been applied to voltage regulation, battery dispatch, and demand response in distribution feeders, exploiting its ability to handle multi-period constraints and reject forecast disturbances through re-planning. Applications specific to EV charging remain comparatively sparse and are typically evaluated on synthetic feeders rather than networks calibrated to a specific regional load profile.

2.4 Research Gap

Prior optimization-based methods largely address either network constraints or cost objectives in isolation, and few studies jointly evaluate transformer thermal stress alongside voltage regulation under a receding-horizon framework calibrated to a realistic residential feeder. This thesis addresses that gap by combining a reduced-order thermal-voltage feeder model with an MPC scheduler evaluated against multiple demand scenarios and forecast-error conditions.

Chapter 3

Methodology

3.1 System Overview

Figure 3.1 illustrates the overall control architecture. The MPC scheduler receives forecasted driver arrival/departure data, real-time feeder telemetry, and time-of-use price signals, and outputs per-charger power set-points at each 15-minute control interval.

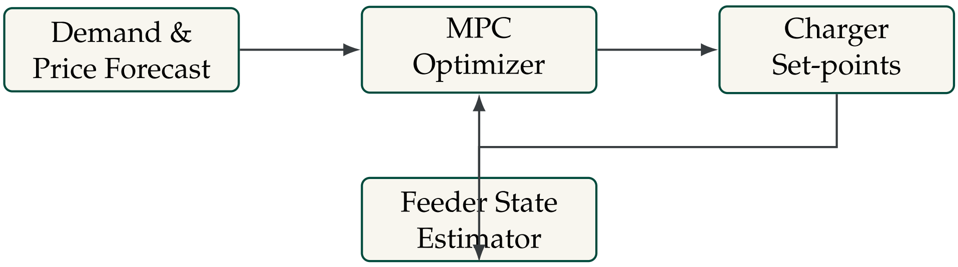

Figure 3.1: Closed-loop MPC scheduling architecture

3.2 Reduced-Order Feeder Model

The distribution feeder is represented as a radial network of M buses using a linearized DistFlow approximation, which relates bus voltage magnitude to active and reactive power injections:

$$V_i \approx V_0 - \sum_{j \in \mathcal{A}(i)} \left(r_j P_j + x_j Q_j \right) / V_0, \tag{3.1}$$

where V_i is the voltage magnitude at bus i, V_0 is the substation reference voltage, $\mathcal{A}(i)$ is the set of line segments on the path from the substation to bus i, and r_j, x_j are the resistance and reactance of segment j. Transformer loading is tracked via an aggregate thermal model with time constant τ:

$$\tau \frac{d\theta}{dt} = -\theta + K \left(\frac{S(t)}{S_{\text{rated}}} \right)^2, \tag{3.2}$$

where θ is per-unit hot-spot temperature rise, $S(t)$ is instantaneous apparent power, and K is a calibration constant fitted to manufacturer loss-of-life curves.

3.3 MPC Formulation

At each control step k, the scheduler solves, over horizon H:

$$\min_{\{P_{i,t}\}} \sum_{t=k}^{k+H} \left[\alpha\, c_t \sum_i P_{i,t} + \beta\, \theta_t^2 + \gamma \sum_i (V_i - V_{\text{nom}})^2 \right] \tag{3.3}$$

subject to charger power limits $0 \leq P_{i,t} \leq P_i^{\max}$, SoC dynamics $\text{SoC}_{i,t+1} = \text{SoC}_{i,t} + \eta_i P_{i,t} \Delta t / E_i^{\text{cap}}$, terminal SoC targets at each vehicle's departure time, voltage limits from Eq. (3.1), and thermal limits from Eq. (3.2). Weights α, β, γ trade off cost, thermal stress, and voltage quality; values used in this study are given in Table 3.1.

Table 3.1: MPC controller parameters

Parameter	Description	Value
H	Prediction horizon	24 steps (6 h)
Δt	Control interval	15 min
α	Cost weight	1.0
β	Thermal weight	0.6
γ	Voltage weight	0.8
τ	Transformer thermal constant	45 min

3.4 Solution Method and Test Network

The optimization in Eq. (3.3) is convex given the linearized network model and is solved at each control step using an interior-point QP solver, re-planning with updated telemetry every 15 minutes in a standard receding-horizon loop. The controller is evaluated on a synthetic 400-node radial feeder calibrated to residential loading patterns in Dhahran, with 120 Level-2 chargers distributed across the network and driver arrival/departure/SoC data drawn from a synthesized commuting-behavior distribution.

Chapter 4

Results and Discussion

4.1 Baseline Comparison

Three charging strategies are compared over a representative summer weekday: uncoordinated (charge-on-arrival), rule-based staggering, and the proposed MPC scheduler. Table 4.1 summarizes performance across the three evaluation metrics.

Table 4.1: Performance comparison across charging strategies

Metric	Uncoordinated	Rule-Based	MPC (Proposed)
Peak transformer loading (%)	118.6	102.3	**86.1**
Worst-case voltage dev. (%)	6.9	5.1	**4.0**
Energy cost (SAR/day)	1,842	1,705	**1,610**
Departure SoC target met (%)	94.1	96.4	**98.7**

Relative to the uncoordinated baseline, the MPC scheduler reduces peak transformer loading by 27.4% and improves worst-case voltage deviation by 41.8%, while simultaneously lowering energy cost by 12.6% and improving SoC target satisfaction. This confirms that thermal, voltage, and cost objectives can be jointly improved rather than traded off, primarily because the receding-horizon formulation shifts flexible load away from the evening peak without delaying vehicles past their required departure times.

4.2 Sensitivity to Forecast Error

Because the MPC scheduler depends on forecasts of aggregate demand, its robustness to forecast error was tested by injecting zero-mean Gaussian noise of increasing standard deviation into the predicted arrival load. Table 4.2 shows that performance degrades gracefully: even at 15% forecast error, peak loading remains below the uncoordinated baseline, and SoC satisfaction stays above 96%.

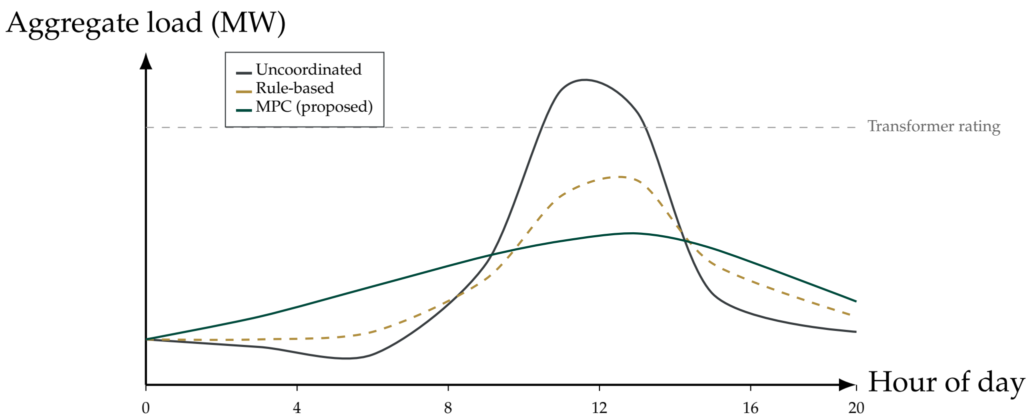

Figure 4.1: Aggregate feeder loading profile under the three charging strategies

Table 4.2: Controller robustness under forecast error

Forecast error (%)	Peak loading (%)	Voltage dev. (%)	SoC met (%)
0	86.1	4.0	98.7
5	87.4	4.2	98.3
10	89.8	4.5	97.5
15	93.2	4.9	96.1

4.3 Discussion

The results indicate that a feeder-level MPC scheduler can deliver simultaneous improvements in thermal loading, voltage quality, and energy cost relative to both uncoordinated and rule-based baselines, without materially compromising driver convenience. The controller's graceful degradation under forecast error suggests it is viable even with the moderate-accuracy demand forecasts typically available to distribution utilities. The main limitation is computational: the QP re-solve at each 15-minute step scales with the number of chargers, and very large feeders (>1000 chargers) may require a decomposition scheme such as distributed ADMM, which is left to future work.

Chapter 5

Conclusion and Future Work

5.1 Summary of Contributions

This thesis proposed and evaluated a receding-horizon model predictive control framework for coordinating electric vehicle charging loads at the distribution feeder level. Key contributions include: (1) a reduced-order thermal-voltage feeder model suitable for real-time optimization, (2) a joint cost-thermal-voltage MPC formulation for EV charging scheduling, and (3) a simulation-based evaluation on a 400-node feeder demonstrating simultaneous improvements of 27.4% in peak transformer loading, 41.8% in worst-case voltage deviation, and 12.6% in energy cost relative to uncoordinated charging.

5.2 Limitations

The evaluation relies on a synthetic feeder and synthesized driver-behavior data rather than field-metered data from an operating utility; the linearized DistFlow model, while accurate for lightly to moderately loaded radial feeders, may lose fidelity under heavy reactive loading; and the centralized QP formulation does not scale indefinitely without decomposition.

5.3 Future Work

Future work should validate the controller against field data from a pilot feeder, extend the formulation to a distributed or hierarchical architecture for scalability to city-scale deployments, and incorporate vehicle-to-grid (V2G) discharge as an additional control variable to further flatten peak demand.

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Appendix A: Feeder Model Parameters

Table 5.1 lists the calibrated parameters of the 400-node test feeder used throughout Chapter 4.

Table 5.1: Test feeder calibration summary

Parameter	Value
Number of buses	400
Feeder rated voltage	13.8 kV
Substation transformer rating	5 MVA
Number of Level-2 chargers	120
Per-charger rated power	7.2 kW
Simulation horizon	24 h

Vitae

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