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OPTIMAL SCHEDULING FOR A FLEET OF ELECTRIC VEHICLES TO BALANCE CHARGING STATION LOAD

By

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This is to certify that:

(i) the report comprises only my original work toward the course project,

(ii) due acknowledgment has been made in the text to all other material used

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Abstract

The abstract of the document is added here...
It is usually written after finishing writing all the other chapters.

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List of Abbreviations

MRSs	Multi-Robot Systems
UAVs	Unmanned Aerial Vehicles
UGVs	Unmanned Ground Vehicles

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1.1 GUC Logo 1

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Chapter 1

Introduction

1.1 Section Name

Some sample text with an Unmanned Aerial Vehicles (UAVs), some citation [**?**, **?**], and some more Unmanned Ground Vehicles (UGVs).

1.2 Another Section

Reference to Section 1.1, and reuse of UGVs nad UAVs with also full use of Multi-Robot Systems (MRSs). Reference to figure 1.1.

Figure 1.1: GUC Logo

Chapter 2

Literature Review

Zhang et al. [1] develop a coordinated framework that links route choice and charging scheduling to reduce travel delays while preventing local grid overloads. The model uses binary assignment variables $Y_{n,m} \in \{0,1\}$ (vehicle n uses station m), continuous charging power $Q_{n,t} \geq 0$, and charging time variables $T_{n,m}$. Their multi-objective goal is expressed as a weighted sum

$$\min\ \mu_1 f_1 + \mu_2 f_2,$$

where f_1 is total travel time and f_2 measures station load imbalance. Practical constraints force a single station per EV ($\sum_m Y_{n,m} = 1$), respect station power limits, and enforce vehicle battery/reachability bounds. The authors solve the multi-EV problem with a Genetic Algorithm (GA) and a Dijkstra-based heuristic for single-EV routing; experiments (Monte Carlo demand traces) show reduced travel time and improved spatial load balance, though the study assumes homogeneous station hardware and omits dynamic pricing.

Mahyari and Freeman [2] model depot charging as a stochastic, epoch-wise Markov decision process. The state includes each vehicle's remaining demand $d_{j,t}$ and due epoch δ_j, and the decisions are assignment binaries $X_{ijkt} \in \{0,1\}$ plus continuous allocations $q_{ijkt} \geq 0$. The immediate epoch cost is

$$C_t(S_t, X_t) = \sum_{i,j,k} e_t\, q_{ijkt},$$

and the global objective is $\min_\pi E\big[\sum_t C_t\big]$ with large penalties for unmet charge at departure. Constraints include one vehicle per connector, per-charger/connector power caps, depot grid cap U, and SoC dynamics $d_{j,t+1} = d_{j,t} - \sum_{i,k} q_{ijkt}$. Their solution uses Approximate Dynamic Programming (ADP) with a linear value-function approximation (VFA) trained by simulation; this yields an online policy that balances immediate cost against approximate future cost, but relies on simulation-based training and careful feature design.

The hierarchical workplace-charging study [3] aims to match EV charging with onsite photovoltaic

(PV) output. Stage 1 finds an aggregate profile $p_{\text{agg},k}$ by minimizing

$$\sum_k (p_{\text{agg},k} - p_{\text{PV},k})^2,$$

subject to bounds $0 \le p_{\text{agg},k} \le P_{\max}\, c_{\text{agg},k}$ and cumulative energy constraints (encoded with an accumulation matrix A). Stage 2 disaggregates p_{agg} to per-vehicle schedules $P_{\text{ind},k}$ using inexpensive heuristics (LLF, EDF) that respect per-vehicle power limits and required energy. The paper introduces clear metrics for PV–EV alignment (self-consumption ϕ_{SC}, self-sufficiency ϕ_{SS} and their balance ϕ_{SCSB}) and shows that the two-stage approach attains near-optimal matching at far lower computation cost than full per-vehicle QP; it assumes reliable PV forecasts and mostly deterministic arrival/departure patterns.

Mavrovouniotis, Ellinas, and Polycarpou [4] target station-level scheduling where service quality is measured by total tardiness

$$f = \sum_{j=1}^{n} \max(0, CT_j - d_j),$$

with $CT_j = s_j + p_j$. The decisions include binary activations $x_{ij} \in \{0, 1\}$ for charging points and start times s_j, and constraints cap simultaneous charges per electrical line and enforce phase-balance (to avoid uneven loading). They apply an Ant Colony System (ACS) where ants construct complete schedules and pheromones guide search; reported parameter settings (e.g., $\alpha = 1, \beta = 5, \rho = 0.4$) produce robust, scalable performance on large instances. The method excels when arrival/departure times are known in advance, but it assumes constant charging rates and a static instance.

Bezzi, Ceselli, and Righini [5] treat the routing problem with multiple charging technologies (each technology h has rate ρ_h and cost γ_h). They use a route-based model with binary route variables x_r and route costs

$$c_r = \sum_{h \in H} \gamma_h\, \delta_{rh},$$

where δ_{rh} is energy recharged on route r using technology h. Constraints ensure customer coverage, fleet-size limits, vehicle capacity, route-duration bounds, and battery feasibility along each route. The main contribution is a Feasible Recharge Polyhedron (FRP) that compactly represents feasible recharge plans and enables efficient label-based dynamic programming in the column-generation pricing step. This exact CG+FRP approach delivers high-quality solutions and precise cost trade-offs between technologies, but can be computationally heavy on large instances; the authors recommend hybridizing with heuristics (e.g., seed routes from GA) for scalability.

Synthesis. Together, these papers provide a complete toolkit: Mahyari & Freeman give a rigorous online/state formulation and a VFA lookahead; Zhang and Mavrovouniotis show how metaheuristics (GA, ACS) can search assignment and scheduling spaces effectively; the workplace study offers a fast hierarchical decomposition for PV alignment; and Bezzi et al. provide exact route-based modeling and the FRP concept for recharge-feasibility checks. For our milestone we can combine the MDP-style state transitions and penalty structure from Mahyari, metaheuristic assignment/scheduling operators from Zhang/ACS, the two-stage PV-matching idea when renewables matter, and FRP-inspired feasibility tests to make route/charging checks fast and accurate.

Chapter 3

Methodology

3.1 Problem Formulation

3.1.1 Overview

The electric vehicle (EV) charging scheduling problem considered in this work aims to optimize the operation of a multi-line charging station that serves a set of EVs within a finite scheduling horizon. Each line in the station consists of several charging spots (or points) that can be simultaneously occupied by different EVs. The goal is to determine, for each EV and at each discrete time slot, (i) which charging spot it occupies (if any) and (ii) at what charging level it operates. The formulation accounts for the limited number of available charging spots, the different charging power levels, and a station-level power constraint. Two conflicting objectives are optimized simultaneously: minimizing the total charging tardiness of all EVs and minimizing the station's peak power demand.

The resulting model can be viewed as a multi-objective, discrete-time, non-preemptive scheduling problem, where each EV must be assigned a contiguous charging interval on one charging spot at a fixed power level.

3.1.2 Sets and Parameters

Symbol	**Description**
$\mathcal{J} = \{1, \ldots, r\}$	Set of electric vehicles (EVs)
$\mathcal{T} = \{1, \ldots, T\}$	Set of discrete time slots of equal duration Δt
$\mathcal{I} = \{1, \ldots, L\}$	Set of charging lines
$\mathcal{S}_i = \{1, \ldots, S_i\}$	Set of charging spots on line i
K	Number of discrete charging power levels
r_ℓ (kW)	Charging power corresponding to level ℓ
E_j^{req} (kWh)	Energy demand of EV j
t_j	Arrival time slot of EV j
d_j	Desired departure (due) time slot of EV j
$p_{j,\ell}$	Number of time slots required to deliver E_j^{req} at level ℓ, $p_{j,\ell} = \lceil E_j^{req}/(r_\ell \Delta t) \rceil$
$P_{\max}$ (kW)	Maximum contracted power for the entire charging station

3.1.3 Decision Variables

Symbol	**Type**	**Description**
$X_{j,i,s,t}$	$\{0, 1\}$	1 if EV j occupies spot s on line i during slot t
$B_{j,\ell,t}$	$\{0, 1\}$	1 if EV j charges at level ℓ during slot t
$\text{Start}_{j,\tau}$	$\{0, 1\}$	1 if EV j begins charging at slot τ
$Tard_j$	$R_{\geq 0}$	Tardiness of EV j beyond its due time
P^{peak}	$R_{\geq 0}$	Peak power consumption of the station

The binary variables $X_{j,i,s,t}$ and $B_{j,\ell,t}$ represent the two main decisions of the optimization problem: (i) the charging spot occupied by each EV in each time slot, and (ii) the charging level applied at that time. Non-preemption is guaranteed by ensuring each EV occupies exactly one contiguous block of slots on a single spot and maintains a constant charging level during its entire session.

3.1.4 Objective Functions

1) Minimization of total tardiness

$$\min f_1 = \sum_{j \in \mathcal{J}} Tard_j \tag{3.1}$$

where

$$Tard_j \geq (CT_j - d_j), \quad \forall j \in \mathcal{J}, \tag{3.2}$$
$$Tard_j \geq 0. \tag{3.3}$$

The completion time CT_j is defined as the last slot in which EV j is charging. This objective ensures that EVs complete their charging as close as possible to their requested departure times.

2) Minimization of station peak power

$$\min f_2 = P^{\text{peak}} \tag{3.4}$$
$$P^{\text{peak}} \geq \sum_{j \in \mathcal{J}} \sum_{\ell=1}^{K} B_{j,\ell,t}\, r_\ell, \quad \forall t \in \mathcal{T}. \tag{3.5}$$

This objective penalizes schedules that cause high instantaneous power demand, encouraging a smoother and more cost-effective power profile for the charging station.

3.1.5 Constraints

(1) Energy requirement:

$$\sum_{t \in \mathcal{T}} \sum_{\ell=1}^{K} B_{j,\ell,t}\, r_\ell\, \Delta t \;\geq\; E_j^{req}, \quad \forall j \in \mathcal{J}.$$

(2) Spot occupancy:

$$\sum_{j \in \mathcal{J}} X_{j,i,s,t} \;\leq\; 1, \quad \forall i \in \mathcal{I},\; s \in \mathcal{S}_i,\; t \in \mathcal{T}.$$

(3) Line capacity:

$$\sum_{s \in \mathcal{S}i} \sum j \in \mathcal{J} X_{j,i,s,t} \;\leq\; S_i, \quad \forall i \in \mathcal{I},\; t \in \mathcal{T}.$$

(4) Station power:

$$\sum_{j \in \mathcal{J}} \sum_{\ell=1}^{K} B_{j,\ell,t}\, r_\ell \;\leq\; P_{\max}, \quad \forall t \in \mathcal{T}.$$

(5) Session–level consistency:

$$\sum_{\ell=1}^{K} B_{j,\ell,t} \;=\; \sum_{i\in\mathcal{I}} \sum_{s\in\mathcal{S}i} Xj,i,s,t, \quad \forall j,\, t.$$

(6) Arrival feasibility:

$$X_{j,i,s,t} = 0, \quad \forall j,\, i,\, s,\, t < t_j.$$

(7) Non-preemption and contiguity: Each EV j occupies a single spot for a contiguous block of slots. In practice, this is enforced via the start variables Startj,τ and the precomputed durations pj,ℓ: if Start$j,\tau = 1$ and $zj,\ell = 1$, then $X_{j,i,s,t} = 1$ for all $t \in [\tau, \tau + p_{j,\ell} - 1]$ on the assigned spot.

3.1.6 Complete Model

The complete multi-objective optimization problem is formulated as:

$$\min_{X,B,z,\text{Start},Tard,P^{\text{peak}}} \quad (f_1, f_2) \tag{3.6}$$

$$\text{s.t.} \quad \text{Constraints (1)–(7)} \tag{3.7}$$

$$X_{j,i,s,t}, B_{j,\ell,t}, z_{j,\ell}, \text{Start}_{j,\tau} \in \{0,1\}, \tag{3.8}$$

$$Tard_j, P^{\text{peak}} \geq 0. \tag{3.9}$$

This formulation explicitly captures the allocation of EVs to charging spots and levels over time while enforcing energy, capacity, and operational constraints. It extends classical EV charging scheduling models by introducing discrete charging-level decisions and a peak-power minimization objective, enabling more flexible and energy-efficient station operation.

Chapter 4

Results

Chapter 5

Conclusion

Chapter 6

Future Work

Appendix

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