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Project Specifications and Preliminary Report on UESTCHN4008P(BEng) Final Year Project

Project Specification and Preliminary Report

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Student Matriculation Number	2959471	Working Title of Project	Smart Charging Scheduling for Cost and Peak Reduction
UESTC Student Number	2023300901028	Name of First Supervisor	Dr Amer Ghias
Degree programme	Communications Engineering (CE)	**Declaration of Originality and Submission Information**	*I affirm that this submission is all my own work in accordance with the University of Glasgow and UESTC Regulations, and the James Watt School of Engineering requirements.* Signed (Student): 谢乐天
Academic year	2026–2027		

Subproject 2 of Design and Development of an AI-Enabled Smart Electric Vehicle Charging and Energy Management Platform

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SP2 will compare charging schedules by electricity cost, peak demand and the energy available before an earlier departure. An optional early energy requirement will be added to the existing LP. The initial study uses software simulation, public charging data and clearly identified synthetic sessions.

Individual contribution

My work covers tariff modelling, charging constraints, baseline strategies, optimisation and the schedule interface. SP1 supplies demand forecasts, SP4 develops the dashboard, and SP5 assesses economic and environmental outcomes. The initial model uses zero solar generation; a solar forecast can be added once SP3 provides an agreed input.

Generative AI acknowledgement

OpenAI Codex assisted with English expression, initial text and code drafts, code organisation and checking, and interpretation of results on 19-22 and 27 October 2026. I take responsibility for the mathematical reasoning, code development and modification, verification of the runs, and review and revision of each section. Synthetic scenarios and the limits of the evaluation are identified in the report.

27 October 2026

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Project Description and Background

Electric vehicles create flexible electricity demand: a vehicle can remain connected longer than the time required to deliver its requested energy. Scheduling can exploit this flexibility, but moving all vehicles to the cheapest hour may simply create a new demand peak. Economic, network and environmental objectives therefore need to be distinguished rather than treated as interchangeable [1], [2].

This project develops the scheduler for Subproject 2 of the team platform. A cost-minimising schedule may defer charging until late in a parking period. If a driver needs the vehicle earlier, little energy may have been delivered. The project asks how a user-declared minimum energy requirement at an earlier time changes cost, peak demand and individual service, while retaining the full request at the planned departure time.

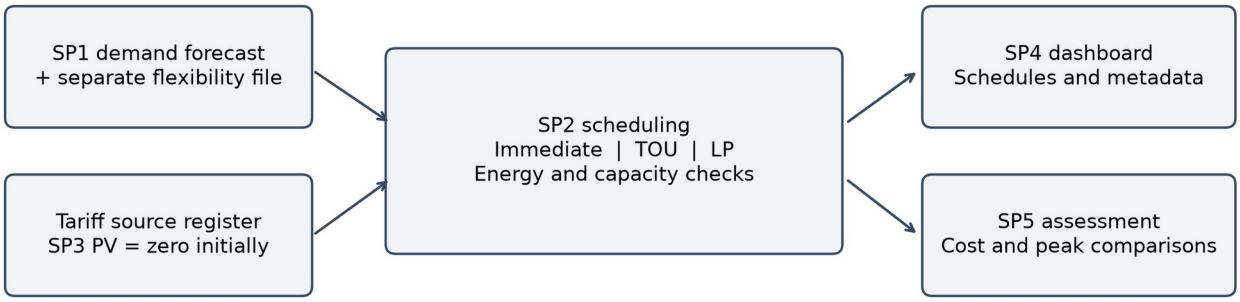


Figure 1 SP2 inputs, decision process and outputs within the team platform

The team has selected City of Boulder charging data for the main study and City of Palo Alto data for validation. SP1 supplies aggregate hourly demand. This forecast does not specify individual energy requests or departure deadlines, so a separate description of charging flexibility is needed. Where session constraints are constructed from incomplete data, the assumptions will be documented alongside the inputs.

The scheduler will be implemented in Python and export CSV schedules with metadata, using UTC timestamps and one-hour intervals. Boulder provides the demand context for a time-of-use benchmark; Palo Alto is assessed with a separate tiered-tariff example. The residential tariffs are modelling scenarios, not verified contracts for the public charging sites. The initial project involves no physical charger control, surveys, participant recruitment or human testing.

Literature Review

Research basis and competing objectives

Mukherjee and Gupta provide an early review of charge scheduling in smart grids [1]. A later review by Aghajan-Eshkevari et al. organises charging and discharging research around control structures, optimisation methods, and economic, network and environmental goals [2]. This distinction matters for SP2: energy cost measures an electricity purchase, peak load measures infrastructure stress, and carbon impact depends on the generation mix. A lower bill alone is not evidence of lower emissions. The present study will report these dimensions separately and leave regional carbon accounting to SP5.

Rotering and Ilic study optimal charge control in deregulated electricity markets [3], establishing a market-oriented strand of the literature. Jin, Tang and Ghosh explicitly distinguish static and dynamic customer charging problems [4]. Their static formulations use linear programming when demands are known in advance; dynamic arrivals require heuristic decisions. For this project, that distinction motivates a deterministic schedule as a transparent reference and a later online extension only after the basic inputs and evaluation are reliable. An offline optimum must not be described as an operational forecast result.

Coordination and load shaping

Gan, Topcu and Low formulate valley filling and develop a decentralised iterative protocol in which vehicles respond to a common utility signal [5]. Their results show why deadlines and charging-rate limits must be embedded in the scheduling problem. The relevance here is the coordination principle: minimising each vehicle's private bill independently can concentrate demand in the same interval. SP2 uses a central site-capacity constraint and an explicit peak term so that the resulting aggregate schedule remains interpretable.

Ma, Callaway and Hiskens model large populations of plug-in vehicles as a non-cooperative game coupled through a common price [6]. Their approach addresses customers making independent charging decisions. SP2 instead assumes a single scheduler with access to the session constraints. This simplifies the optimisation but limits the conclusions: the model cannot establish customer acceptance or describe strategic responses to prices. Those questions would require a model of individual decision-making and further evidence.

From ideal schedules to operational constraints

The Adaptive Charging Network described by Lee et al. combines convex optimisation with model predictive control and addresses practical issues including three-phase infrastructure, non-ideal battery behaviour and quantised charging signals [7]. Its use of recorded workloads and explicit baseline comparisons is especially relevant. SP2 adopts the discipline of constraint checking and reproducible comparison, while retaining a deliberately simpler hourly continuous-power model. The resulting peak is an hourly average and cannot be equated with a utility's shorter demand-metering interval.

Ferragut, Narbondo and Paganini analyse how uncertain departure times affect the service obtained under earliest-deadline-first and least-laxity-first charging [8]. Their study shows why individual attained service matters alongside aggregate performance. SP2 will examine a simpler declared early energy requirement, then test departures around that time. The contribution is its implementation and evaluation in the team platform; departure uncertainty and the added linear constraint are not claimed as new algorithms.

Literature Review continued

Learning approaches and evaluation data

Wan et al. formulate real-time charging as a Markov decision process and use deep reinforcement learning [9]. This approach can adapt to uncertain prices and behaviour, but requires a training environment and constraint handling. The initial SP2 study uses an explicit LP so its service requirements and failure cases can be checked directly.

Zhao et al. review reinforcement-learning approaches and open questions in charging scheduling [10]. This research moves towards sequential decisions under uncertainty. SP2 first establishes deterministic baselines and evaluates departure perturbations; learning-based control remains a possible later extension rather than a requirement for the initial study.

ACN-Data distinguishes connection, disconnection, delivered energy and user requests [11]. These fields illustrate why aggregate hourly demand alone cannot determine charging flexibility. The team retains its Boulder and Palo Alto datasets; any reconstructed windows or early energy preferences will be labelled as assumptions. Observed disconnection times will not be treated as advance knowledge available to a real-time planner.

Table 1 Comparison of research directions and the proposed use in SP2

Approach and sources	Strength for this task	Limitation and SP2 response
Static LP and market control [3], [4]	Explicit energy, cost and availability constraints	Known-input assumption; use as an offline reference
Decentralised coordination [5], [6]	Coordinates many flexible loads	Different information/agent model; no equilibrium claim
Convex scheduling with MPC [7]	Updates schedules and models operational limits	Requires online inputs; defer until fixed-horizon validation
Deep RL and review [9], [10]	Sequential decisions with uncertain dynamics	Training and constraint burden; defer learning
Public session data [11]	Observable charging events support reproducibility	Missing requests remain assumptions; publish a field audit

Project gap and selected direction

The selected extension allows a session to specify an early readiness time and a minimum charging energy by that time. The original LP remains the reference; immediate charging and the TOU heuristic provide additional comparisons. Tests will vary early requirements, site capacity and peak weight, and record infeasible requests. Actual departure perturbations will be withheld from the planner. A declared minimum is conditional on model feasibility and the vehicle remaining connected until its readiness time.

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SMART Objectives

Objective	Completion evidence and target date
1 Specify and validate inputs	By 13 November 2026: document tariffs, hourly session inputs, early readiness fields and flexibility assumptions; reject invalid units, windows and missing rates.
2 Verify baseline and extended schedules	By 11 December 2026: provide immediate, TOU, original LP and early-energy LP schedules; check energy, availability, power limits and infeasible requests against hand-calculated cases.
3 Evaluate cost and service trade-offs	By 19 February 2027: evaluate at least 30 daily windows, three capacities and three peak weights; vary early targets and departure perturbations, reporting cost, peak, service and runtime.
4 Deliver the team interface	By 26 March 2027: provide validated CSV/meta outputs and session service summaries for SP4/SP5 review; complete the poster by 16 April and dissertation by 28 April.

Technical Background

Model and information boundary

The horizon contains T one-hour intervals of duration Δt. Session i has arrival a_i, exclusive departure d_i, grid-side energy request E_i and maximum power P_i. The decision p_{it} is grid-side power. An optional readiness time r_i satisfies $a_i < r_i \leq d_i$, with minimum energy q_i between zero and E_i. Neither energy request represents battery state of charge or guaranteed driving range.

Aggregate forecasts do not supply session constraints. The early-energy prototype therefore uses eight synthetic sessions connected from 14:00 to 22:00, each requesting 14 kWh with a 7 kW limit. Site capacity is 28 kW with eight available connections. This constructed example checks the formulation; it does not establish fleet behaviour or field performance. Background load and PV are initially zero.

Linear optimisation formulation

The objective is electricity cost plus λz, where z is maximum hourly site load. The weight λ, in USD/kW over the evaluation horizon, controls the emphasis on peak reduction; it is not a utility demand charge. Setting $\lambda = 0$ minimises energy cost. The constraints are:

$0 \leq p_{it} \leq P_i$ within $[a_i, d_i)$; $p_{it} = 0$ outside that window.
$\Sigma_t\, p_{it}\, \Delta t = E_i$ for every session.
$\Sigma_i\, p_{it} \leq z \leq$ Psite for every interval.
Objective: $\Sigma_t\, c_t\, (\Sigma_i\, p_{it})\, \Delta t + \lambda z$.

For the extended LP, cumulative energy over $a_i \leq t < r_i$ must also be at least q_i. The full-energy equality remains in force. Missing early requirements recover the original feasible set. Infeasible requests are reported rather than silently relaxed. In the eight-session example with $\lambda = 0$, requiring 7 kWh per vehicle by 18:00 increases full-plan energy cost from USD 14.21532 to USD 18.69840; both plans deliver 112 kWh and peak at 28 kW.

Technical Background continued

Tariffs and fair comparison

Schedules use UTC interval starts, converted to the utility's local timezone for tariff classification. The July 2023 Boulder benchmark uses America/Denver and Xcel RE-TOU rates [12]. Weekday mid-peak runs from 13:00 to 15:00 and on-peak from 15:00 to 19:00; other hours, weekends and listed holidays are off-peak [13]. Earlier pilot hours differ, so 2018 has a separate profile. Each rate snapshot has a stated date; observed substitute holidays still need verification before historical bill reconstruction.

For Palo Alto E-1, the first tier is 11 kWh multiplied by the number of metering days, rather than a new allowance for each vehicle every day [14]. With fixed total energy and background consumption in one billing period, shifting energy in time alone produces no tiered energy-cost saving. The initial implementation uses the proposed 2020 council-packet rates as a labelled scenario; final adoption and a complete historical rate series remain to be verified. Site electricity purchases and public charging operator prices are separate quantities.

All four methods use identical sessions, power limits and tariffs. Report full-plan energy cost, peak power, early-target attainment, individual shortfalls, infeasibility and runtime. Immediate charging is capacity-limited FIFO; the TOU heuristic allocates the cheapest slots in departure order. A failed heuristic is recorded as a failure. Cost comparisons retain equal delivered energy; lower expenditure caused by an early departure and curtailed charging is not an efficiency saving.

Hypotheses and evaluation protocol

H1: with $\lambda = 0$, the original LP has no greater cost than any feasible schedule meeting the same full requests. H2: tightening an early requirement cannot improve the optimal cost-plus-peak objective, although cost and peak separately may move either way. H3: an admitted early requirement is met at readiness under the model assumptions; leaving sooner may produce a shortfall. No fixed improvement percentage is assumed.

Validation covers hand calculations, energy conservation, power limits and infeasibility. Evaluation will use at least 30 daily windows, three capacities and three peak weights, with early targets of 25%, 50% and 75% of requested energy. Readiness times and actual departure perturbations are distinct inputs: only the former are known to the planner. The illustrative LP comparison uses the same max-min early-service tie-break in both methods. Input hashes, tariff versions, assumptions and solver results will be retained.

Security and ethical considerations

Following the Engineering Council's security guidance, deliberate or malicious harm is considered separately from accidental failure [15]. Threats include altered tariffs, malformed CSVs, exposed credentials and misleading outputs. Controls include schema and range validation, source hashes, local simulation, versioned outputs and keeping tokens and meeting links out of the public repository. Raw user identifiers will not be redistributed. Environmental claims require region-matched factors and an explicit accounting boundary; this subsystem will not infer carbon savings from a lower tariff.

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Measurable Outcomes and Work Plan

The project will deliver a tariff register, validated inputs, three baseline strategies and the LP extension with early energy requirements. Outputs include hourly schedules and session-level service summaries for SP4/SP5. Checks cover full and early energy, power limits, reproducible costs and explicit failures. The comparison will quantify the cost of providing earlier energy, rather than assume the extension always saves money.

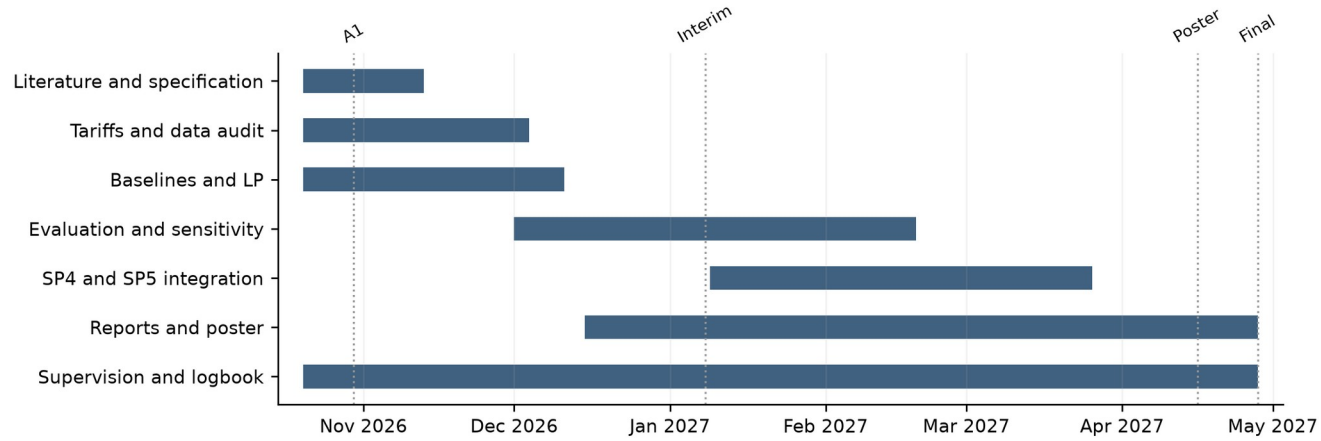


Figure 2 Planned work to April 2027; LP development includes early energy requirements

Work package	Planned hours	Completion evidence
Literature and specification	40	Comparison matrix; A1 report by 30 October
Data and tariff validation	35	Source ledger and explicit coverage gaps
Baselines and early energy	65	Tested original and extended LP; constraint checks
Evaluation and sensitivity	70	Cost and service trade-offs; failure analysis
Integration and documentation	35	SP4/SP5 can read and reproduce outputs
Reports and presentation	55	Interim 8 January; poster 16 April; final 28 April
Supervision and logbook	20	Dated genuine records and action tracking

The planned workload is 320 hours. Early-energy modelling is included in the optimisation and evaluation work packages. The main dependencies are tariff coverage and session flexibility data. Evaluation starts with synthetic scenarios and extends to verified input windows. The zero-PV assumption remains until a solar input is agreed. Integration is scheduled for 26 March, leaving time for the dissertation, poster and oral assessment.