

Design and Development of Electric Vehicle Charging Station Infrastructure Integrated with a Solar PV-Based Microgrid for Traffic-Responsive Load Management

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Abstract

The rapid proliferation of electric vehicles (EVs) is placing an increasingly non-uniform and spatially concentrated demand on distribution networks, particularly at public electric vehicle charging stations (EVCS) situated along high-traffic urban corridors. Uncoordinated charging at such locations can produce sharp power demand peaks, voltage deviations, and elevated dependency on grid-supplied energy, while simultaneously under-utilizing the significant rooftop and canopy area available for distributed solar photovoltaic (PV) generation. This paper presents the design and development of an EVCS infrastructure integrated with a solar PV-based microgrid in which the charging power allocation and battery schedule are governed by road traffic conditions, referred to here as traffic-responsive load management (TRLM). The proposed architecture combines a rooftop/canopy-mounted PV array with maximum power point tracking (MPPT), a battery energy storage system (BESS) interfaced through a bidirectional DC-DC converter, a grid-tied bidirectional inverter, and multiple Level-2 and DC fast-charging points, all coordinated by a centralized Energy Management System (EMS). An upstream traffic sensing layer estimates a Traffic Density Index (TDI); its few-minute detection-to-arrival lead time is used for fast power allocation, while a TDI forecast built from the site's historical profile and corrected in real time is used to plan a battery reserve and a grid peak-shaving threshold ahead of the commute peaks. Mathematical models are developed for the PV array, battery state-of-charge dynamics with separate charge and discharge efficiencies, the microgrid power balance, a calibrated Poisson EV arrival process with an explicit pass-by capture fraction and lead time, class-wise queue stability, and the traffic-anticipatory dispatch. A Monte Carlo time-series simulation (300 independent days,

1-min resolution, common random numbers) compares TRLM with a fully specified time-of-use/SOC rule-based baseline operating under identical physical constraints. TRLM increases the PV self-consumption ratio by 8.4 percentage points (95% CI 7.9 - 8.9), reduces the grid dependency ratio by 3.9 points and reduces the mean daily evening 15-min peak grid demand by 10.9 kW (12.1%), with the battery kept within its 20% - 90% SOC band; waiting time during high-traffic intervals is essentially unchanged (-0.16 min) and daily energy cost rises by 0.9%. The findings indicate that coupling distributed solar generation, battery storage and traffic forecasting at the EVCS level is a technically viable means of reducing coincident evening peak loading, with a benefit that depends on forecast quality and on the evening energy deficit relative to battery capacity.

Keywords

Electric Vehicle Charging Station, Solar Photovoltaic Microgrid, Battery Energy Storage System, Traffic-Responsive Load Management, Energy Management System, Peak Load Shaving, Smart Grid, Sustainable Transportation

1. Introduction

A. Background and Motivation

The transportation sector is undergoing a fundamental transition from internal combustion engine (ICE) vehicles toward electric vehicles (EVs), driven by policy mandates on carbon emissions, declining battery costs, and growing consumer acceptance. This shift is placing new and substantial demands on electric power distribution networks, particularly at public electric vehicle charging stations (EVCS) located along arterial roads, highway rest areas, and urban intersections where vehicle throughput is high and highly time-variant.

Conventional EVCS installations are typically supplied entirely from the utility grid and operate with static or first-come-first-served charging schedules that do not account for the instantaneous availability of renewable generation or the stochastic nature of vehicle arrivals. As EV adoption accelerates, uncoordinated charging at high-traffic locations can produce sharp, coincident power demand peaks that stress local transformers and feeders, increase system losses, and in some cases require costly network reinforcement [1].

At the same time, the canopy and rooftop area associated with charging forecourts represents an underexploited opportunity for distributed solar photovoltaic (PV) generation. When combined with a battery energy storage system (BESS), a solar-integrated EVCS can operate as a small-scale microgrid capable of supplying a significant fraction of its own energy needs, reducing peak grid import, and providing a degree of resilience during grid disturbances [2]. However, solar generation is intermittent and diurnal, while EV charging demand is governed by

traffic patterns that vary by time of day, day of week, and local road conditions. Without an intelligent coordination layer, the mismatch between PV generation availability and traffic-driven charging demand limits the achievable benefits of such integration.

This paper addresses this gap by proposing a traffic-responsive load management (TRLM) strategy for a solar PV-integrated EVCS microgrid, in which real-time road traffic density data is used to modulate charging priority, power allocation, and energy dispatch decisions, so that the available solar and stored energy are used more effectively while respecting vehicle service-level expectations.

B. Problem Statement and Research Gap

Existing solar-integrated EVCS designs generally optimize energy dispatch using only internal state variables such as battery SOC, time-of-use electricity tariffs, or historical average charging demand [3]. These approaches do not explicitly incorporate live traffic conditions as an input to the energy management decision process, even though traffic density, measured upstream of the station and forecast from its historical pattern, is a leading indicator of near-term EV arrival rate and, therefore, of the charging power that will shortly be required. As a result, conventional EMS designs may under-allocate solar and battery resources during periods that are about to experience a surge in charging demand, or may unnecessarily draw from the grid during low-traffic periods when deferring non-urgent charging would allow greater self-consumption of solar energy. There is, therefore, a need for an EVCS energy management framework that fuses traffic-sensing data with solar generation forecasts and battery state information to make forward-looking, traffic-aware charging and dispatch decisions.

C. Contributions

This paper makes the following contributions: 1) a system architecture for solar PV-integrated EVCS microgrids that explicitly incorporates a real-time traffic sensing layer as an EMS input, rather than treating traffic only as a planning-stage siting consideration; 2) a formal mathematical definition of the Traffic Density Index (TDI) and its use in a Poisson-based EV arrival-rate model that links road traffic conditions to anticipated charging demand; 3) a priority-weighted, traffic-aware power allocation algorithm that dynamically balances vehicle waiting time, state-of-charge deficit, and traffic density to coordinate PV, battery, and grid resources; and 4) a Monte Carlo evaluation (300 independent days with common random numbers, 95% confidence intervals and paired tests) against a fully specified rule-based baseline under identical physical constraints, showing statistically significant improvements in PV self-consumption, grid dependency and evening peak grid demand, with service quality essentially unchanged.

D. Scope and Paper Organization

This study focuses on the system-level design, mathematical modeling, and simulation-based evaluation of a single traffic-responsive solar-EVCS microgrid node. The traffic sensing layer is represented through an aggregated Traffic Density Index derived from vehicle count data rather than through detailed micro-

scopic traffic simulation, and the analysis operates at the power-flow and energy-management time scale (one minute to one hour resolution); power-quality phenomena, protection coordination, and detailed converter switching dynamics are outside the present scope. The remainder of the paper is organized as follows. Section II reviews related work on EV charging infrastructure, solar-integrated microgrids, and demand-responsive load management. Section III presents the proposed system architecture. Section IV develops the mathematical models underlying the PV subsystem, battery subsystem, microgrid power balance, and traffic-responsive charging allocation algorithm. Section V describes the simulation setup and case-study parameters. Section VI presents and discusses the simulation results relative to a baseline strategy. Section VII concludes the paper and outlines directions for future work.

2. Related Work

A. Electric Vehicle Charging Infrastructure

Public EV charging infrastructure is generally classified into Level-1 (single-phase AC, low power), Level-2 (AC, 3.3 - 22 kW), and DC fast-charging (50 - 350 kW) categories. Fast-charging stations, in particular, impose large instantaneous power demands on the distribution network because multiple vehicles may charge simultaneously for short periods. Numerous studies have examined the impact of uncoordinated EV charging on distribution transformer loading, feeder voltage profiles, and network losses [4]-[7], generally concluding that coordinated or smart charging strategies are necessary as EV penetration increases [8]. Time-of-use tariff scheduling and direct load control have both been proposed as coordination mechanisms [5] [9] [10], but these approaches primarily respond to price or utility signals rather than to the physical availability of on-site renewable generation.

B. Solar PV Integration with EVCS

Several works have investigated co-locating solar PV generation with EVCS to offset grid energy consumption [11]-[13], typically using canopy-mounted or carport-integrated PV arrays sized to the forecourt footprint. Rule-based energy management strategies are commonly employed, wherein PV generation is prioritized for direct consumption by connected EVs, with any surplus routed to battery storage or exported to the grid. While these designs demonstrably reduce grid energy import, most rely on relatively simple heuristics (e.g., first-come-first-served or fixed priority ordering) that do not anticipate near-term surges in charging demand associated with traffic patterns, and therefore may not fully exploit the available solar resource during transitional periods.

C. Battery Energy Storage in EVCS Microgrids

Battery energy storage systems are widely adopted in solar-EVCS microgrids to decouple the timing of solar generation from that of charging demand, enabling energy generated during low-traffic daylight hours to be used during subsequent high-traffic periods. The literature on BESS sizing and dispatch for EVCS appli-

cations generally optimizes for objectives such as peak shaving, arbitrage against time-of-use tariffs, or minimization of battery degradation through SOC-constrained cycling [14]-[16]. State-of-charge feedback control remains the dominant dispatch mechanism; comparatively fewer studies incorporate external, forward-looking signals such as traffic density to pre-emptively manage battery state ahead of anticipated demand surges.

D. Traffic-Responsive and Demand-Responsive Load Management

Traffic flow data has been applied in the EV charging literature primarily for infrastructure planning purposes, such as determining optimal EVCS siting and sizing along road networks based on historical or predicted traffic volumes [17]-[20]. Its use as a real-time input to the operational energy management of an already-deployed EVCS is comparatively less explored. Related work in demand-responsive load management for buildings and industrial microgrids demonstrates that incorporating leading indicators of load (such as occupancy sensors or production schedules) into EMS decision-making can improve resource utilization relative to reactive, state-feedback-only control [15] [21]. This paper extends this concept to the EVCS domain by treating road traffic density as a leading indicator of near-term charging demand.

E. Research Gap

Based on the reviewed literature, existing solar-integrated EVCS energy management strategies predominantly react to internally measured quantities (battery SOC, PV output, connected EV state) or to externally imposed price signals, but do not explicitly incorporate real-time road traffic density as a forward-looking demand indicator for operational dispatch. **Table 1** summarizes representative approaches from the literature alongside the proposed work, highlighting this gap.

Table 1. Comparison of representative EVCS energy management approaches.

Ref.	Approach	PV Integration	Real-Time Traffic Input	Remarks
[5]	Grid-only EVCS with time-of-use scheduling	No	No	Reduces cost via tariff scheduling only
[11]	Solar-integrated EVCS with rule-based EMS	Yes	No	Improves self-consumption; static charging priority
[14]	PV-battery microgrid with SOC-based dispatch	Yes	No	Focuses on battery cycling and degradation
[9]	Demand-response EVCS using price signals	No	No	Responds to price, not to real-time traffic
[18]	Optimal EVCS siting using traffic flow data	No	Partial (planning stage only)	Traffic used for location, not real-time dispatch
[22]	Forecast-based EV charging scheduling (ML)	No	Partial (historical demand)	Uses historical charging demand, not live traffic
Proposed	Solar PV-BESS EVCS microgrid with real-time TRLM	Yes	Yes (real-time)	Couples live TDI with priority-weighted dispatch

This gap motivates the traffic-responsive load management framework developed in Sections III and IV, in which a live Traffic Density Index is fused with battery SOC and solar generation forecasts within a unified priority-weighted power allocation algorithm.

3. System Architecture and Methodology

A. Overview of the Proposed System

The proposed infrastructure is a grid-connected solar PV-battery microgrid dedicated to electric vehicle charging, in which the power allocation among the solar array, battery energy storage, and the utility grid is coordinated by a centralized Energy Management System (EMS) that receives, in addition to standard electrical measurements, a real-time traffic density signal from a roadside sensing layer. **Figure 1** shows the overall system architecture, and the corresponding traffic-responsive control logic is presented in Section IV. The system comprises five principal subsystems: i) the solar PV generation subsystem, ii) the battery energy storage subsystem, iii) the grid interconnection subsystem [23], iv) the EVCS charging subsystem, and v) the traffic sensing and EMS control layer.

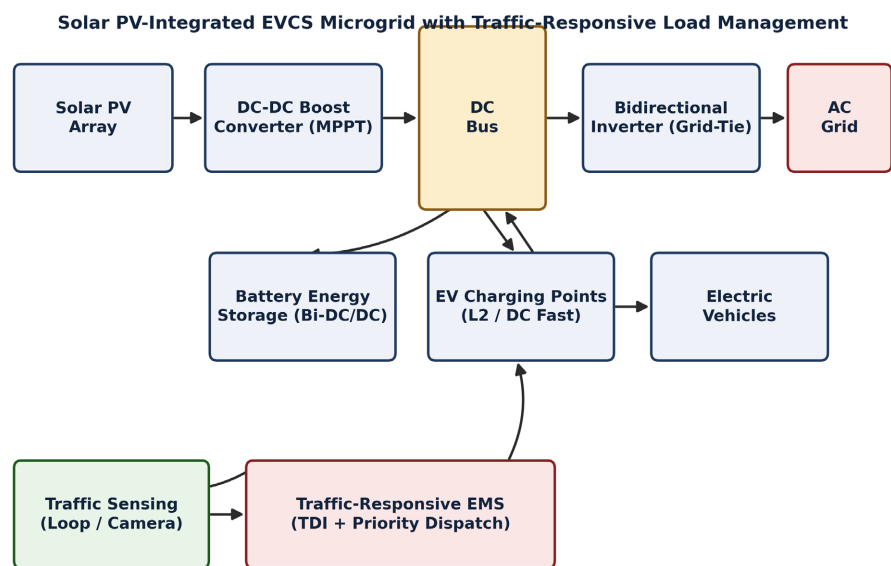


Figure 1. Block diagram of the proposed solar PV-integrated EVCS microgrid with traffic-responsive energy management.

B. Solar PV Subsystem

The PV subsystem consists of a canopy-mounted monocrystalline PV array feeding a DC-DC boost converter operated under Perturb-and-Observe (P&O) maximum power point tracking (MPPT). The boost converter regulates the array output onto a common DC bus at nominal 600 V, from which power is distributed to the battery converter, the EVCS charge points, and the grid-tied inverter. The rated specifications of the PV subsystem adopted for this study are summarized in **Table 2**.

Table 2. Solar pv subsystem specifications.

Parameter	Value
Module type	Monocrystalline silicon
Rated power per module	550 Wp
Module efficiency (η_{pv})	18.0%
Open-circuit voltage (V_{oc})	49.8 V
Short-circuit current (I_{sc})	13.9 A
Temp. coefficient of power (β_T)	-0.35%/°C
NOCT	45 ± 2°C
Total array area (A_{pv})	500 m ² (canopy)
Rated array capacity	90 kWp

C. Battery Energy Storage Subsystem

The battery energy storage system (BESS) is interfaced to the DC bus through a bidirectional DC-DC converter, allowing it to absorb surplus PV generation during low-traffic, high-irradiance periods and to discharge to support EVCS demand during high-traffic periods or after sunset. The BESS is operated within a restricted SOC band to preserve battery health and to retain reserve capacity for demand surges anticipated from the traffic forecast (Section IV-D). **Table 3** summarizes the adopted BESS specifications.

Table 3. Battery energy storage system specifications.

Parameter	Value
Chemistry	LiFePO ₄
Rated energy capacity (E_{batt})	150 kWh
Rated charge/discharge power	75 kW (0.5°C)
Round-trip efficiency (η_{batt})	95% ($\eta_c = \eta_d = 97.47\%$)
SOC operating range	20% - 90%
Nominal DC bus voltage	600 V
Expected cycle life (80% DOD)	6000 cycles

D. EVCS Charging Subsystem

The charging subsystem provides a mix of Level-2 AC and DC fast-charging points [24] to accommodate vehicles with different dwell times, consistent with observed usage patterns at high-traffic corridor locations where a subset of drivers require rapid top-up charging. **Table 4** lists the charging point configuration used in the case study of Sections V and VI.

Table 4. Evcs charging point configuration.

Type	Qty	Rated (each)	Aggregate
Level-2 AC	4	7.2 kW	28.8 kW
DC fast charge	2	50 kW	100 kW
Total	6	-	128.8 kW

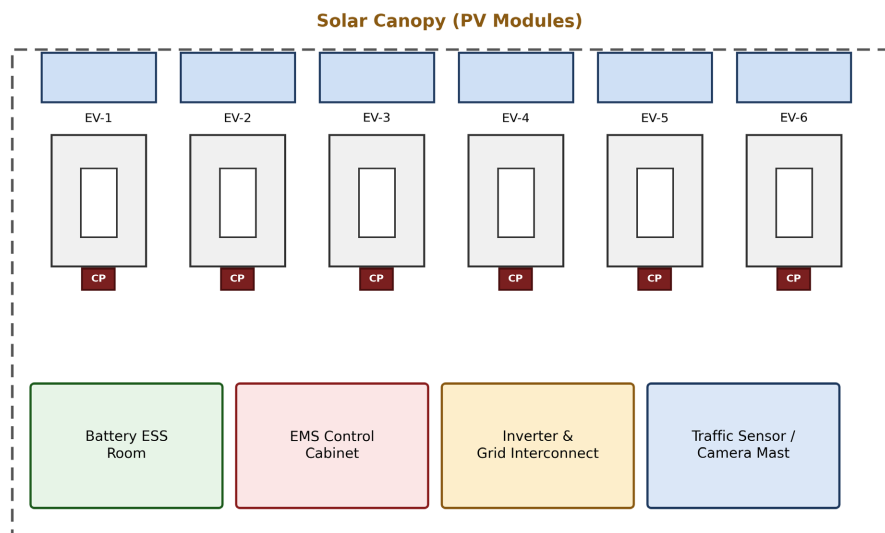
The ratings in **Table 4** are DC-bus input ratings; the energy delivered to a vehicle is 95% of the charger input (charger efficiency). The aggregate Level-2 rating is $4 \times 7.2 \text{ kW} = 28.8 \text{ kW}$, and the total EVCS input rating is therefore 128.8 kW.

E. Traffic Sensing and Data Acquisition Layer

The traffic sensing layer consists of inductive loop detectors and/or camera-based vehicle counting units installed on the approach roadway to the EVCS, together with an edge-processing unit that aggregates raw vehicle counts into a rolling traffic density estimate $\rho(t)$, expressed in vehicles per hour. This measurement is transmitted to the EMS at a fixed sampling interval (adopted as $\Delta t = 5$ minutes in this study) and forms the basis of the Traffic Density Index (TDI) developed in Section IV-D.

The detector is installed $d_s = 1.5 \text{ km}$ upstream of the station entrance on the approach carriageway, so that a counted vehicle reaches the forecourt after a lead time τ_L of approximately 2.6 - 4.8 min (Section IV-D); the detector speed measurement is used to estimate τ_L online. Because this lead time is of the same order as the 5-min reporting interval, the measured TDI is used only for fast power allocation and operating-mode selection. Battery scheduling ahead of the commute peaks relies instead on a TDI forecast constructed from the historical traffic profile of the site and corrected in real time (Section IV-D).

F. Energy Management System Architecture

**Figure 2.** Schematic physical layout of the proposed solar-integrated EVCS facility.

The EMS is implemented as a supervisory control layer that executes, at each

sampling interval, a four-stage decision process: 1) data acquisition from the PV, battery, grid, and traffic sensing subsystems; 2) computation of the Traffic Density Index and the associated EV arrival-rate estimate; 3) classification of the current traffic state and selection of the corresponding charging priority mode; and 4) solution of the power allocation problem to dispatch PV, battery, and grid power to individual charge points. This decision process, and its underlying mathematical formulation, is described in detail in Section IV. **Figure 2** provides an illustrative physical layout of the proposed facility, showing the relative arrangement of the solar canopy, charging bays, battery room, EMS control cabinet, grid inter-connection equipment, and the traffic sensor mast.

4. Mathematical Modeling

This section develops the mathematical models that describe the behaviour of the solar PV subsystem, the battery energy storage subsystem, the overall microgrid power balance, the traffic-responsive EV demand model, and the charging priority and power allocation algorithm that constitutes the core contribution of this paper.

A. Photovoltaic Array Model

The current-voltage characteristic of a PV cell is represented using the single-diode equivalent circuit model [25], given by

$$I = I_{ph} - I_0 \left[\exp \left(\frac{q(V + IR_s)}{nkT} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \quad (1)$$

where I is the output current, I_{ph} is the photo-generated current, I_0 is the diode saturation current, q is the electron charge, R_s and R_{sh} are the series and shunt resistances respectively, n is the diode ideality factor, k is Boltzmann's constant, and T is the cell temperature in Kelvin. The operating cell temperature is estimated from ambient temperature and irradiance using the Nominal Operating Cell Temperature (NOCT) model:

$$T_c(t) = T_a(t) + \frac{\text{NOCT} - 20}{800} G(t) \quad (2)$$

where $T_a(t)$ is the ambient temperature and $G(t)$ is the plane-of-array solar irradiance. For system-level energy balance studies, the PV array output power is more conveniently represented using an empirical thermally-derived efficiency model:

$$P_{pv}(t) = \eta_{pv} A_{pv} G(t) [1 - \beta_T (T_c(t) - T_{ref})] \quad (3)$$

where η_{pv} is the rated module efficiency, A_{pv} is the total array area, β_T is the power temperature coefficient, and T_{ref} is the reference cell temperature (25°C). The boost converter maintains the DC bus voltage according to the standard boost relation

$$V_{dc} = \frac{V_{pv}}{1 - D} \quad (4)$$

where V_{pv} is the PV array terminal voltage, V_{dc} is the regulated DC bus voltage,

and D is the converter duty cycle set by the MPPT controller.

B. Battery Energy Storage Model

The battery state of charge is modelled using a discrete-time Coulomb-counting formulation:

$$\text{SOC}(t + \Delta t) = \text{SOC}(t) + \frac{[\eta_c P_{\text{batt, ch}}(t) - P_{\text{batt, dis}}(t)/\eta_d] \Delta t}{E_{\text{batt}}^{\text{rated}}} \quad (5)$$

$$P_{\text{batt}} = P_{\text{batt, ch}} - P_{\text{batt, dis}}, \quad P_{\text{batt, ch}} P_{\text{batt, dis}} = 0, \quad \eta_c = \eta_d = \sqrt{\eta_{rt}} \quad (5a)$$

where $P_{\text{batt, ch}}(t) \geq 0$ and $P_{\text{batt, dis}}(t) \geq 0$ are the charging and discharging powers at the DC-bus terminals of the battery converter, $P_{\text{batt}}(t)$ is their difference (positive during charging), η_c and η_d are the one-way charging and discharging efficiencies derived from the round-trip efficiency $\eta_{rt} = 95\%$ of **Table 3** ($\eta_c = \eta_d = 0.9747$), and $E_{\text{batt}}^{\text{rated}}$ is the rated energy capacity of the battery. Charging power is multiplied by η_c and discharging power is divided by η_d , so that the energy withdrawn from the cells during discharge always exceeds the energy delivered to the DC bus, and a complete charge-discharge cycle returns $\eta_c \eta_d = \eta_{rt}$ of the energy absorbed. The complementarity condition in (5a) excludes simultaneous charging and discharging. To preserve battery health and reserve capacity, the SOC and battery power are constrained as

$$\text{SOC}_{\min} \leq \text{SOC}(t) \leq \text{SOC}_{\max}, \quad -P_{\text{batt}}^{\max} \leq P_{\text{batt}}(t) \leq P_{\text{batt}}^{\max} \quad (6)$$

where $\text{SOC}_{\min}$ and $\text{SOC}_{\max}$ define the permissible operating band and $P_{\text{batt}}^{\max}$ is the maximum charge/discharge power rating of the battery converter.

C. Microgrid Power Balance

At every instant, the instantaneous power balance of the DC-coupled microgrid must be satisfied:

$$P_{\text{pv}}(t) + P_{\text{grid}}(t) + P_{\text{batt, dis}}(t) = P_{\text{EVCS}}(t) + P_{\text{batt, ch}}(t) + P_{\text{loss}}(t) \quad (7)$$

where $P_{\text{grid}}(t)$ is positive when importing from the utility grid and negative when exporting, and $P_{\text{loss}}(t)$ represents converter and conductor losses. The aggregate EVCS demand is the sum of the individual charge-point power allocations:

$$P_{\text{EVCS}}(t) = \sum_{i=1}^{N(t)} P_{\text{ch}, i}(t) \quad (8)$$

where $N(t)$ is the number of vehicles connected and actively charging at time t , and $P_{\text{ch}, i}(t)$ is the power delivered to the i -th vehicle.

D. Traffic-Responsive EV Demand Model

The Traffic Density Index (TDI) normalizes the measured road traffic density $\rho(t)$ against the historically observed maximum traffic density ρ_{max} for the site:

$$\text{TDI}(t) = \frac{\rho(t)}{\rho_{\text{max}}}, \quad \text{TDI}(t) \in [0, 1] \quad (9)$$

The expected EV arrival rate at the station is modelled as a base arrival rate modulated linearly by the TDI measured at the upstream detector, with the traffic-observation-to-arrival lead time τ_L made explicit:

$$\lambda(t + \tau_L) = \lambda_{\text{base}} [1 + k_\lambda \text{TDI}(t)] \quad (10)$$

where λ_{base} is the part of the arrival rate that does not depend on passing traffic (destination and local demand), k_λ is the traffic-sensitivity coefficient, and τ_L is the lead time between a vehicle being counted at the detector and its arrival at the forecourt. With the detector placed d_s upstream of the station entrance, τ_L is estimated from the detector speed measurement (dual-loop or camera tracking) as the travel time over d_s plus the entry and manoeuvring delay τ_d measured at the forecourt entrance:

$$\tau_L(t) = \frac{d_s}{\bar{v}(t)} + \tau_d, \quad \bar{v}(t) = v_{\text{ff}} [1 - 0.6 \text{TDI}(t)] \quad (10a)$$

where $\bar{v}(t)$ is the mean approach speed, represented here by a linear speed-density relation with free-flow speed $v_{\text{ff}} = 60$ km/h, $d_s = 1.5$ km and $\tau_d = 1$ min. This gives $\tau_L \approx 2.6$ min in free flow and 4.1 - 4.8 min for $\text{TDI} = 0.85 - 1.0$. Because the edge processor reports the TDI as a 5-min aggregate (Section III-E), the reporting latency (up to 5 min) is of the same order as τ_L . A contemporaneous traffic count therefore provides essentially no usable lead for battery scheduling; it is used for the fast (1-min) power allocation and the operating mode of **Table 5**, while the anticipatory battery action is derived from the traffic forecast (10d) described below.

Equation (10) can be written in terms of the absolute traffic flow as

$$\lambda(t) = \lambda_{\text{base}} + f_p \rho(t), \quad f_p = \frac{k_\lambda \lambda_{\text{base}}}{\rho_{\text{max}}} = s_{\text{EV}} p_{\text{stop}} \quad (10b)$$

where f_p is the pass-by capture fraction, *i.e.*, the fraction of passing vehicles that seek charging at the station, which may be decomposed into the EV share of passing traffic s_{EV} and the probability p_{stop} that a passing EV stops to charge. With $\rho_{\text{max}} = 900$ veh/h, $\lambda_{\text{base}} = 1.6$ sessions/h and $k_\lambda = 1.5$, $f_p = 0.27\%$ (for example, $s_{\text{EV}} = 5\%$ and $p_{\text{stop}} = 5.3\%$). The model therefore assumes a constant pass-by capture fraction; the overall ratio $\lambda(t)/\rho(t)$ decreases as traffic increases because the λ_{base} component does not scale with ρ .

Calibration procedure. λ_{base} and k_λ are estimated from historical charging-session records (session start times from the charge-point management system, *e.g.*, OCPP logs) aligned with the detector data. The detector TDI series is first shifted by $\tau_L(t)$ from (10a); session counts n_j and lag-aligned mean TDI values x_j are then formed for hourly bins j , and the parameters are obtained by Poisson maximum-likelihood regression with an identity link:

$$(\hat{\lambda}_{\text{base}}, \hat{b}) = \arg \max_j \sum_j [n_j \ln(\lambda_{\text{base}} + b x_j) - (\lambda_{\text{base}} + b x_j)], \quad \hat{k}_\lambda = \hat{b} / \hat{\lambda}_{\text{base}} \quad (10c)$$

with confidence intervals obtained from the observed Fisher information (delta method for k_λ). Field records for the case-study site are not yet available, so the values in **Table 6** are design assumptions. The procedure was verified on 30 days (720 hourly bins) of synthetic records generated with the assumed parameters; it recovered $\hat{\lambda}_{\text{base}} = 1.55$ sessions/h (95% CI 1.35 - 1.75), $\hat{k}_\lambda = 1.56$ (1.01 - 2.11) and $\hat{f}_p = 0.27\%$ (0.21% - 0.33%), consistent with the generating values. The sensitivity of the results to k_λ is reported in Section VI-E.

Traffic forecast. For battery scheduling, the EMS forecasts the TDI over a rolling 24-h horizon from the historical same-weekday profile TDI_{hist} of the site, corrected in real time by an exponentially smoothed ratio of the measured to the historical TDI:

$$\begin{aligned}\widehat{\text{TDI}}(t+h) &= \text{TDI}_{\text{hist}}(t+h) \left[1 + (c(t)-1)e^{-h/H} \right], \\ c(t) &= (1-\beta)c(t-\Delta t) + \beta \frac{\text{TDI}(t)}{\text{TDI}_{\text{hist}}(t)}\end{aligned}\quad (10d)$$

where h is the forecast horizon, $\beta = 0.2$ is the smoothing factor (updated every 5 min) and $H = 120$ min is the horizon over which the real-time correction decays to the historical profile. Over the evening ramp (16:00 - 19:30) of the simulated days, the 60-min-ahead mean absolute TDI error of (10d) was 0.054, compared with 0.272 when the contemporaneous TDI is used as the prediction (persistence); this quantifies why a contemporaneous count alone cannot support anticipation of the evening peak. The number of vehicle arrivals within a sampling interval Δt is treated as a Poisson-distributed random process:

$$P(N(t) = n) = \frac{(\lambda(t)\Delta t)^n e^{-\lambda(t)\Delta t}}{n!} \quad (11)$$

Together, (10)-(11) give the expected near-term charging load for a given measured or forecast traffic state; this expectation is used by the reserve planning of Section IV-E, so that the battery is prepared before the vehicles arrive rather than reacting only after they have connected.

E. Charging Priority and Power Allocation Algorithm

Each connected vehicle i is assigned a dynamic priority weight $w_i(t)$ that combines its waiting time, its current SOC deficit, and the prevailing traffic density index, reflecting the intuition that under high traffic density, faster turnaround becomes more valuable to overall throughput:

$$w_i(t) = \alpha_1 \frac{1}{t_i^{\text{wait}}} + \alpha_2 \frac{1}{\text{SOC}_i(t)} + \alpha_3 \text{TDI}(t), \quad \alpha_1 + \alpha_2 + \alpha_3 = 1 \quad (12)$$

where t_i^{wait} is the elapsed waiting/charging time of vehicle i , $\text{SOC}_i(t)$ is its current state of charge, and $\alpha_1, \alpha_2, \alpha_3$ are weighting coefficients selected by the system operator (subject to summing to unity). The available EVCS power, drawn from the combined PV, battery, and grid resources, is then distributed among connected vehicles in proportion to their normalized priority weight, subject to each vehicle's rated charger power and remaining energy requirement:

$$P_{\text{ch},i}(t) = \min \left(P_i^{\text{rated}}, \frac{(\text{SOC}_i^{\text{tgt}} - \text{SOC}_i(t))E_i}{\eta_i \Delta t_i^{\text{rem}}} \right) \frac{w_i(t)}{\sum_{j=1}^{N(t)} w_j(t)} P_{\text{EVCS}}^{\text{avail}}(t) \quad (13)$$

where P_i^{rated} is the rated power of the charge point serving vehicle i , $\text{SOC}_i^{\text{tgt}}$ is its target state of charge, E_i is its battery capacity, η_i is its charging efficiency, Δt_i^{rem} is its estimated remaining connection time, and $P_{\text{EVCS}}^{\text{avail}}(t)$ is the total power available for allocation to the EVCS at time t . The overall dispatch objective min-

minimizes the net cost of grid energy exchange over the operating horizon T , subject to the constraints of Equations (6), (7), and (13):

$$\min C_{\text{total}} = \sum_{t=1}^T [c_{\text{grid}}(t) P_{\text{grid}}(t) - c_{\text{sell}}(t) P_{\text{exp}}(t)] \Delta t \quad (14)$$

where $c_{\text{grid}}(t)$ and $c_{\text{sell}}(t)$ are the time-varying grid import price and export/feed-in price respectively, and $P_{\text{exp}}(t)$ is any surplus power exported to the grid. Equations (6)-(14) collectively define the traffic-responsive load management (TRLM) algorithm executed by the EMS at each control interval, as summarized in the flowchart of **Figure 3**.

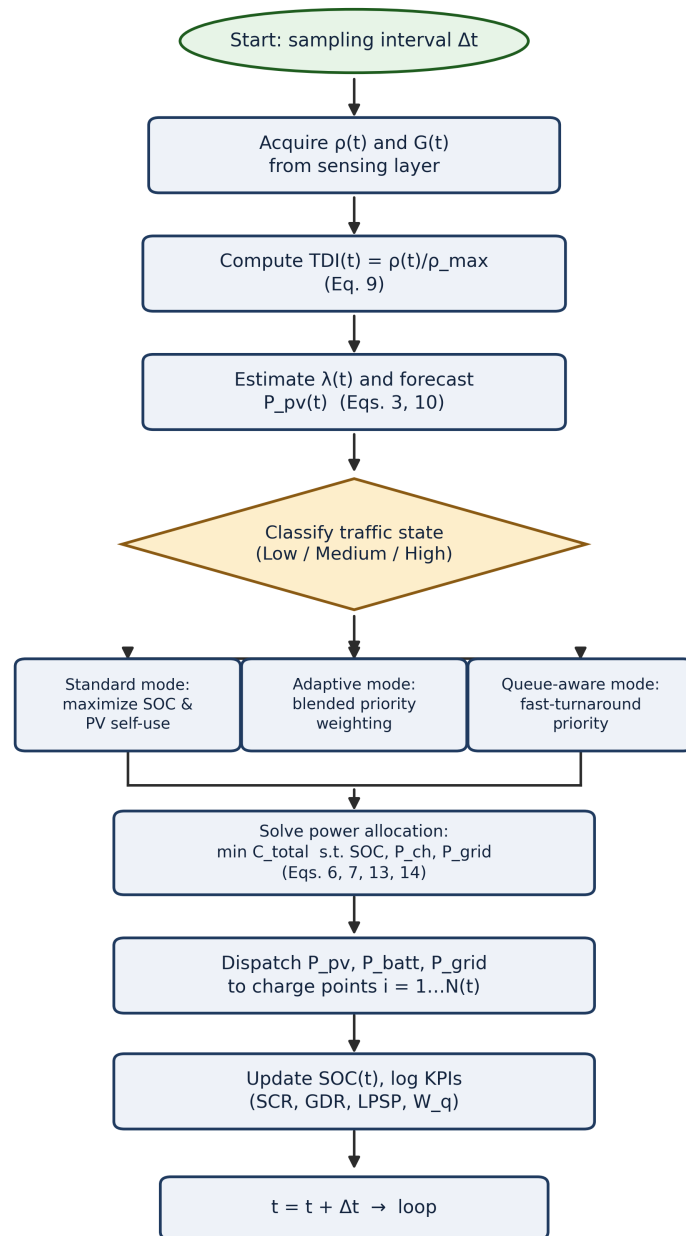


Figure 3. Flowchart of the traffic-responsive load management (TRLM) algorithm executed by the EMS.

Traffic-anticipatory reserve and peak-shaving threshold. In the implementation evaluated here, the objective (14) is realized by a rule-based planner that is resolved every 60 min on 5-min blocks over a rolling 24-h horizon. For the forecast TDI of (10d), the conditional expectations of the EVCS load exceedance and of the PV surplus are read from look-up tables built from historical EVCS load records (60 days in this study), and the reserve SOC that must be held at each time, so that the battery can keep grid import at or below a threshold P_{thr} throughout the forecast high-demand period, is obtained by backward recursion:

$$SOC_{res}(t) = \min \left\{ SOC_{max}, \max \left[SOC_{min}, SOC_{res}(t + \Delta t) + \frac{(\gamma \hat{P}_{exc}(t)/\eta_d - \eta_c \hat{P}_{sur}(t)) \Delta t}{E_{batt}^{rated}} \right] \right\} \quad (14a)$$

$$\begin{aligned} \hat{P}_{exc}(t) &= E \left[\max(P_{EVCS} - P_{pv} - P_{thr}, 0) | \widehat{TDI}(t) \right], \\ \hat{P}_{sur}(t) &= E \left[\max(P_{pv} - P_{EVCS}, 0) | \widehat{TDI}(t) \right] \end{aligned} \quad (14b)$$

where $\gamma = 1.1$ is a safety margin. P_{thr} is the smallest threshold, found by bisection, for which the reserve trajectory is attainable from the current SOC without exceeding SOC_{max} . The complete dispatch rules of the TRLM and baseline strategies, which share identical physical constraints, are given in Section V-B.

F. Performance Evaluation Metrics

To evaluate the effectiveness of the proposed TRLM strategy relative to a non-traffic-responsive baseline, the following performance metrics are defined. The PV self-consumption ratio (SCR) quantifies the fraction of generated solar energy consumed locally rather than exported:

$$SCR = \frac{\int_0^T \min(P_{pv}(t), P_{load}(t)) dt}{\int_0^T P_{pv}(t) dt} \times 100\% \quad (15)$$

The grid dependency ratio (GDR) quantifies the fraction of total EVCS energy demand supplied from the utility grid:

$$GDR = \frac{\int_0^t P_{grid}(t) dt}{\int_0^t P_{EVCS}(t) dt} \times 100\% \quad (16)$$

The loss of power supply probability (LPSP) quantifies the fraction of EVCS demand that cannot be met by the combined PV, battery, and grid supply within converter and connection limits, and is used as a reliability indicator:

$$LPSP = \frac{\sum_{t=1}^T [P_{EVCS}(t) - P_{supply}(t)]}{\sum_{t=1}^T P_{EVCS}(t)} \quad (17)$$

Finally, queue stability is verified separately for the two charger classes, since a vehicle can only be served by a charge point of its own class:

$$\rho_k(t) = \frac{\lambda_k(t)}{c_k \mu_k} < 1, \quad \mu_k = \frac{1}{E[t_{ch,k}] + \tau_{oh}}, \quad k \in \{L2, DC\} \quad (18)$$

where λ_k is the arrival rate of class k ($\lambda_{DC} = 0.6\lambda$, $\lambda_{L2} = 0.4\lambda$), c_k is the number of charge points of class k , $E[t_{ch,k}]$ is the mean charging time at rated power, including the DC taper over the last 40% of the requested energy, and $\tau_{oh} = 3$ min is the plug-in, authorization and departure overhead. A time-varying queue remains stable over a peak only if $\rho_k < 1$ with margin; (18) is therefore used as a design check, whereas the waiting times reported in Section VI are measured directly in the discrete-event simulation (arrival to plug-in, first-come-first-served within each class), which remains valid for the time-varying, non-exponential service of the case study. These metrics—SCR, GDR, LPSP, evening peak grid demand and waiting time—are used in Section VI to compare the proposed TRLM strategy with the baseline strategy.

5. Simulation Setup and Case Study

A. Simulation Environment and Assumptions

The proposed system and the TRLM algorithm developed in Section IV were evaluated through a Monte Carlo time-series simulation. Each replication covers 48 h, a 24-h warm-up followed by a 24-h evaluation day, so that the metrics are not influenced by the assumed initial SOC of 50%. Power flows, vehicle charging and queues are simulated with a 1-min step, while the EMS updates the TDI measurement, forecast correction and operating mode every $\Delta t = 5$ min and re-plans the reserve every 60 min. The EVCS microgrid is located at a high-traffic urban arterial road and sized according to **Tables 2-4**. Two strategies are compared under identical solar and traffic inputs and identical physical constraints: i) a baseline, non-traffic-responsive rule-based strategy, and ii) the proposed TRLM strategy; both are fully specified in Section V-B.

B. Dispatch Rules and Common Physical Constraints

Common constraints (both strategies). (a) The power balance (7) is enforced at every 1-min step. (b) Charger input limits follow **Table 4**: 7.2 kW per Level-2 point and 50 kW per DC point, the DC power tapering linearly to 25 kW over the last 40% of the requested energy; charger efficiency is 95% and the total EVCS input cannot exceed 128.8 kW. (c) The BESS limits of (6) apply (± 75 kW, $SOC_{min} = 20\%$, $SOC_{max} = 90\%$) with the efficiency accounting of (5). (d) The grid connection is limited to 100 kW import and 60 kW export at the AC point of connection, with 97% inverter efficiency; PV surplus beyond the battery and export limits is curtailed. (e) PV serves the EVCS load first, then charges the BESS, and is exported last. (f) The BESS may be charged from the grid only in the off-peak window 00:00 - 06:00. (g) The BESS always discharges, down to SOC_{min} , whatever part of the deficit exceeds the grid import limit, so charging is curtailed only when PV, BESS and grid together cannot meet the requested power. (h) Vehicles queue first-come-first-served within their charger class and plug in when a charge point of that class becomes free.

Baseline strategy. The baseline is a time-of-use/SOC-feedback rule set that uses no traffic information. (B1) During the peak-tariff window 12:00 - 20:00, the BESS

discharges to cover any deficit between the EVCS load and PV, down to SOC_{min} . (B2) Outside this window it discharges only under rule (g). (B3) In the off-peak window it is charged from the grid to a fixed target SOC of 60%, leaving headroom for midday PV. (B4) When the available power is insufficient, it is allocated first-come-first-served by arrival time, each vehicle up to its acceptance limit.

Proposed TRLM strategy. (T1) During 12:00 - 20:00, the BESS discharges to cover the deficit only down to the planned reserve $SOC_{res}(t)$ of (14a), or down to SOC_{min} when the measured TDI indicates the High state of **Table 5**. (T2) At any time, it discharges the part of the deficit that would raise grid import above the planned threshold P_{thr} , down to SOC_{min} . (T3) In the off-peak window, it is charged from the grid to the reserve required at 06:00 by (14a) instead of a fixed target. (T4) Curtailed power is shared according to the normalized priority weights of (12)-(13). Rules (a)-(h) apply unchanged, so the two strategies differ only in their use of traffic information.

C. Input Profiles

A stochastic solar irradiance profile was generated for each replication from a clear-sky envelope between sunrise (06:00) and sunset (18:00), with a peak of 1000 W/m^2 , multiplied by a two-state Markov cloud process (day-level cloud-onset probability 0.01 - 0.04 per minute, clearing probability 0.12 per minute, attenuation depth 0.35 - 0.80); ambient temperature varies between 26°C and 40°C . The corresponding PV array power, computed using (2)-(3) with a 98% MPPT converter efficiency, is shown in **Figure 4**.

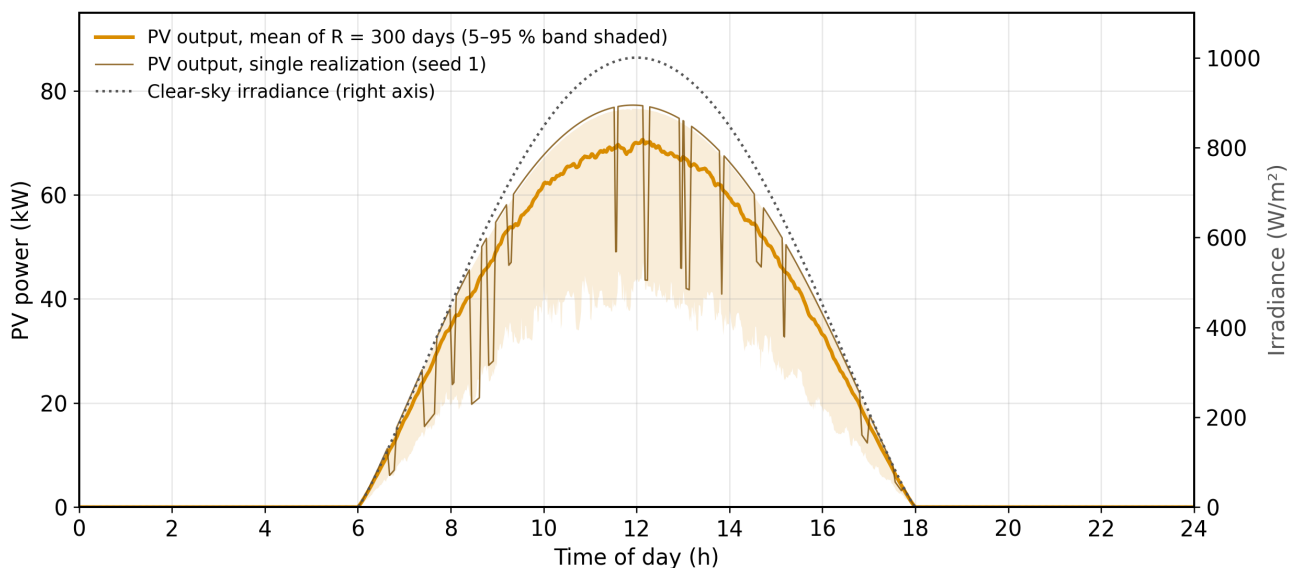


Figure 4. Clear-sky irradiance envelope and PV array output power: mean and 5% - 95% band over $R = 300$ simulated days, and one realization.

The historical road traffic density profile has two characteristic peaks corresponding to the morning (approximately 08:00 - 09:30) and evening (approximately 17:30 - 19:00) commute periods, consistent with typical urban arterial traffic patterns. For each replication, the historical profile is scaled by a day-level fac-

tor (normal, mean 1, standard deviation 0.08), the evening peak is shifted by a uniformly distributed offset of up to ± 15 min, and a first-order autoregressive fluctuation (coefficient 0.97, stationary standard deviation of about 6%) is superimposed; the TDI is normalized with $\rho_{\max} = 900$ veh/h. The resulting EV arrival rate, derived using (10), is shown in **Figure 5** together with the service capacity obtained from (18).

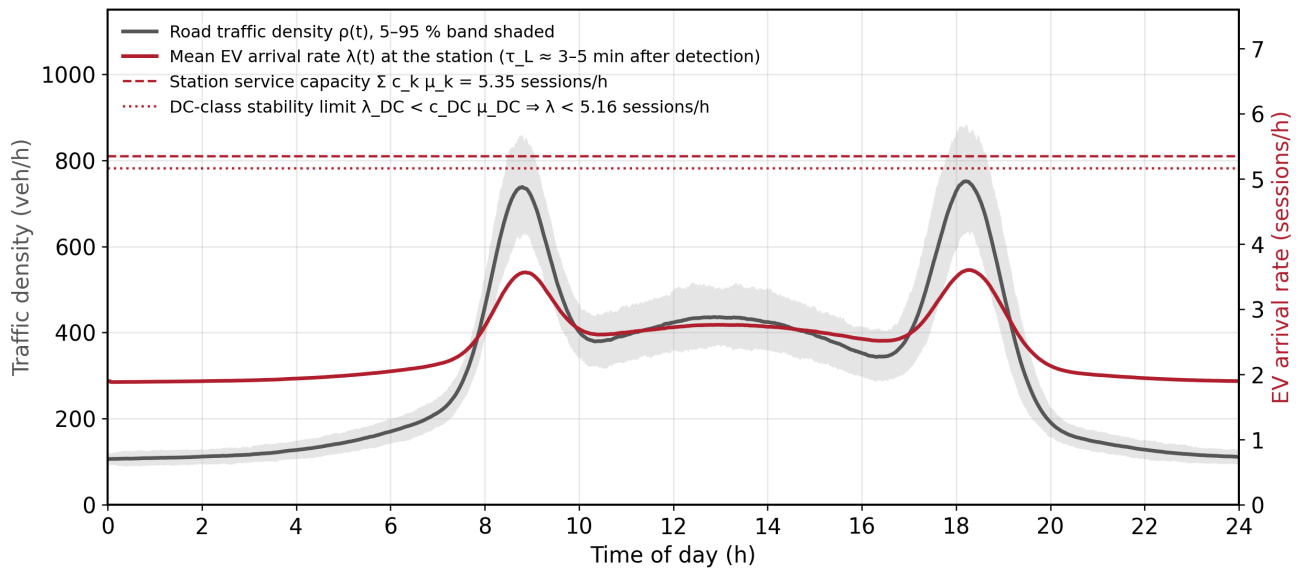


Figure 5. Road traffic density (mean and 5% - 95% band) and mean EV arrival rate at the station, with the station service capacity and the DC-class stability limit from (18).

Table 5. Traffic density index classification and corresponding ems operating mode.

Traffic State	TDI Range	EMS Response
Low	$\text{TDI}(t) < 0.35$	Standard charging priority; maximize SOC and PV self-consumption
Medium	$0.35 \leq \text{TDI}(t) < 0.70$	Adaptive/blended priority; balance turnaround speed and cost
High	$\text{TDI}(t) \geq 0.70$	Queue-aware, fast-turnaround mode; prioritize short waiting time

D. Simulation Parameters

Table 6. Case study simulation parameters.

Parameter	Value
Simulation horizon	48 h per replication (24-h warm-up + 24-h evaluation day)
Time steps	1 min (power flow, queue); $\Delta t = 5$ min (EMS); 60 min (reserve re-planning)
PV array rated capacity	90 kWp
Battery rated capacity / power	150 kWh/ ± 75 kW
Battery SOC range	20% - 90% (initial 50%)
BESS efficiencies (η_c, η_d)	0.9747, 0.9747 ($\eta_{rt} = 95\%$)

Continued

Total EVCS rated capacity	128.8 kW (4×7.2 kW + 2×50 kW)
Grid import / export limit	100 kW/60 kW (inverter efficiency 97%)
Baseline EV arrival rate (λ_{base})	1.6 sessions/h
Traffic sensitivity coeff. (k_t)	1.5 (sensitivity: 1.0 and 2.0)
Historical max. traffic density (ρ_{max})	900 veh/h
Pass-by capture fraction (f_p)	0.27%
Detector distance / lead time (d_s/τ_L)	1.5 km/2.6 - 4.8 min
Charger class split	60% DC, 40% Level-2
Avg. energy requested/session	DC 24 kWh; Level-2 12 kWh (gamma, shape 4, clipped to $0.3 - 1.9 \times \text{mean}$)
Connection overhead (τ_{oh})	3 min
Grid import price (peak/off-peak)	0.18/0.09 \$/kWh (peak 12:00 - 20:00)
Grid export (feed-in) price	0.05 \$/kWh
Off-peak BESS grid charging	00:00 - 06:00; baseline target SOC 60%
Priority weights ($\alpha_1, \alpha_2, \alpha_3$)	0.4, 0.3, 0.3
Monte Carlo replications (R)	300 (numpy SeedSequence 20260915)

E. Monte Carlo Design and Statistical Analysis

Each strategy is evaluated on $R = 300$ independent days. The random streams of replication r (irradiance, traffic, arrivals and session energies) are generated from child r of numpy SeedSequence(20260915), and the same stream is used for both strategies (common random numbers), so that differences arise from the dispatch alone. The look-up tables used by the TRLM planner were built from 60 separate days (Seed Sequence(1)), so that planning and evaluation data are disjoint. For each metric M , the per-day paired difference $d_r = M_r^{\text{TRLM}} - M_r^{\text{base}}$ is formed, and results are reported as the mean with the 95% confidence interval

$$\bar{d} \pm t_{0.975, R-1} \frac{s_d}{\sqrt{R}}, \quad d_r = M_r^{\text{TRLM}} - M_r^{\text{base}}, \quad r = 1, \dots, R \quad (19)$$

where $\bar{d}$ and s_d are the sample mean and standard deviation of d_r . Two-sided paired t-test and Wilcoxon signed-rank p-values are also reported. The evening peak grid demand is the largest 15-min mean import between 16:00 and 21:00 of each day, and the high-traffic waiting time is the mean waiting time (arrival to plug-in) of vehicles arriving while $\text{TDI} \geq 0.70$.

6. Results and Discussion*A. Battery State of Charge Behaviour*

Figure 6 compares the battery SOC over the evaluation day. Under the baseline, the BESS is grid-charged to 60% overnight, reaches a mean of about 87% around noon, and is discharged throughout the peak-tariff window whenever the EVCS load exceeds PV, so that on most days it approaches SOC_{min} by 18:00 - 19:00, before the end of the evening traffic peak. Under TRLM, overnight charging is limited to the reserve required by (14a); the lower morning SOC leaves headroom to absorb the midday PV surplus, and the forecast-based reserve holds energy until the evening peak, after which the SOC is drawn down. In both strategies the SOC remained within the 20% - 90% band on all 300 days because the band is enforced as a hard constraint; the mean daily SOC range was 20.0% - 89.0% for the baseline and 20.0% - 82.8% for TRLM. The anticipation visible in **Figure 6** results from the traffic forecast (10d) and the reserve (14a), not from the contemporaneous TDI.

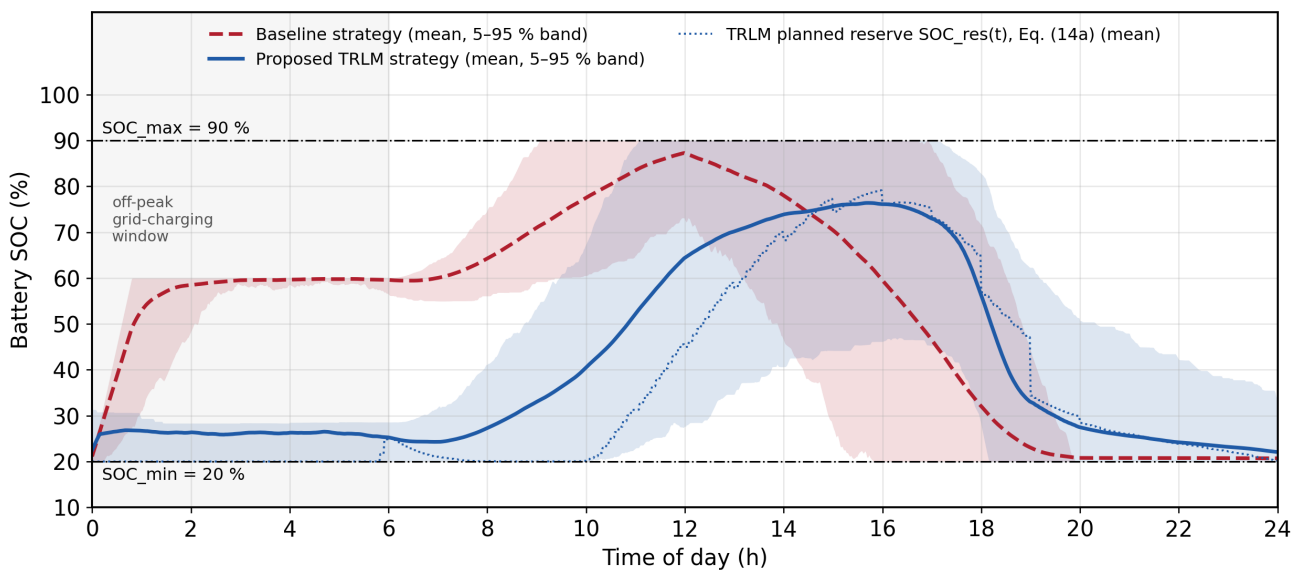


Figure 6. Battery SOC (mean and 5% - 95% band over $R= 300$ days) for the baseline and TRLM strategies, with the TRLM planned reserve $SOC_{res}(t)$.

B. Grid Power Demand Comparison

Figure 7(a) compares the 15-min mean grid import. In both strategies, grid import is bounded by the 100-kW connection limit and never exceeds the 128.8-kW EVCS input rating; the power balance (7) and all limits of Section V-B were verified at every time step. The baseline import rises in the early hours because of off-peak BESS charging and again in the evening once the battery is depleted. TRLM imports more between 13:00 and 17:00, while it holds the reserve, and less during the evening peak. Because the timing of the evening peak varies from day to day, the difference is clearer in the distribution of the daily evening peak, **Figure 7(b)**: the baseline reaches the 100-kW connection limit on most days (median 100 kW), whereas the TRLM median is about 82 kW, and TRLM gives a lower evening peak on 67% of the days.

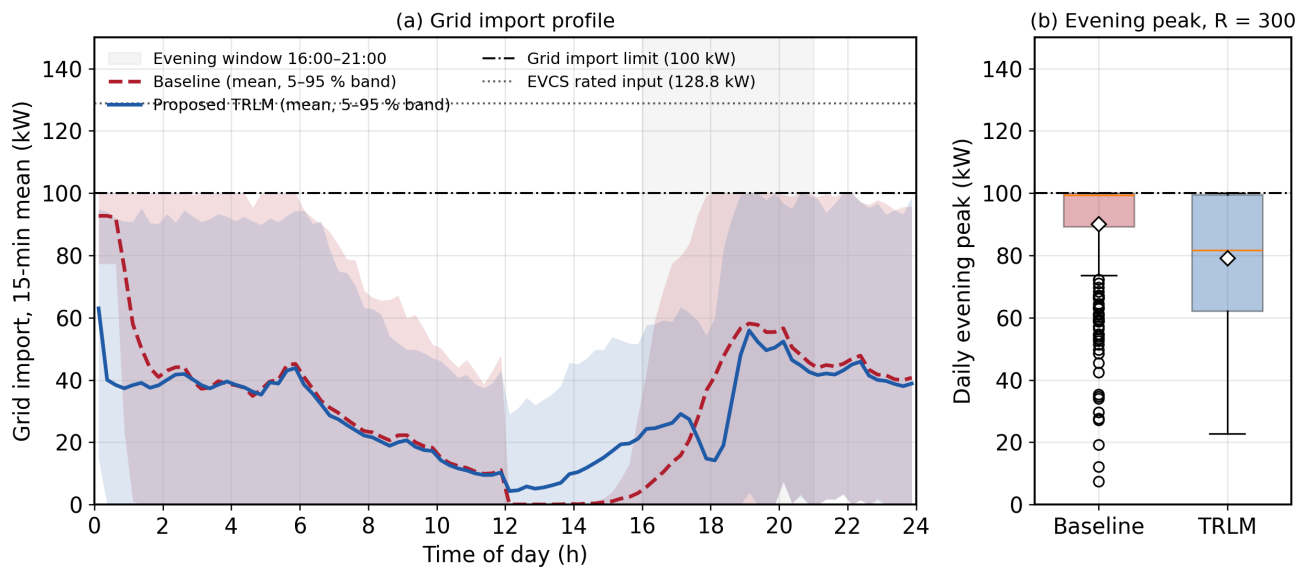


Figure 7. (a) Grid import (15-min mean; mean and 5% - 95% band over $R = 300$ days) for the baseline and TRLM strategies; (b) distribution of the daily evening (16:00 - 21:00) peak grid import (box: interquartile range; line: median; diamond: mean).

C. Summary of Performance Metrics

Table 7. Performance comparison: baseline vs. proposed traffic-responsive strategy (mean over $R = 300$ days with 95% confidence interval).

Metric	Baseline	Proposed TRLM	Paired difference [95% CI]; p
PV self-consumption ratio (SCR)	84.6% [83.3, 85.8]	93.0% [92.0, 93.9]	+8.4 pp [7.9, 8.9]; $p < 0.001$
Grid dependency ratio (GDR)	62.0% [61.4, 62.6]	58.1% [57.4, 58.7]	-3.9 pp [-4.2, -3.7]; $p < 0.001$
Evening peak grid demand (15-min, 16:00 - 21:00)	90.1 kW [88.1, 92.1]	79.2 kW [77.0, 81.5]	-10.9 kW [-12.5, -9.2] (-12.1%); $p < 0.001$
Daily peak grid demand (15-min)	99.6 kW [99.4, 99.8]	95.8 kW [94.9, 96.8]	-3.8 kW [-4.6, -3.0]; $p < 0.001$
Loss of power supply probability	1.14% [1.02, 1.27]	1.03% [0.92, 1.15]	-0.11 pp [-0.19, -0.03]; $p = 0.007$
Avg. vehicle waiting time (high traffic)	7.19 min [6.15, 8.23]	7.03 min [6.01, 8.06]	-0.16 min [-0.25, -0.07]; $p < 0.001$
Avg. vehicle waiting time (all day)	6.00 min [5.46, 6.54]	6.00 min [5.46, 6.54]	0.00 min [-0.05, 0.05]; $p = 0.96$
95th-percentile waiting time	34.4 min [31.8, 37.0]	34.6 min [32.0, 37.2]	+0.2 min [-0.1, 0.6]; $p = 0.21$
Daily grid energy cost	\$76.4 [74.1, 78.8]	\$77.1 [74.7, 79.5]	+\$0.69 [0.32, 1.06] (+0.9%); $p < 0.001$
Battery SOC range (mean daily min - max)	20.0% - 89.0%	20.0% - 82.8%	Within 20% - 90% on all days (both)

p: two-sided paired t-test; Wilcoxon signed-rank tests give the same conclusions at the 5% level for every metric (daily cost: $p = 0.033$). Throughput was identical for both strategies (58.3 sessions/day, 6.5 of them in high-traffic intervals).

D. Discussion

The Monte Carlo results show statistically significant paired improvements

in the solar and grid metrics when a traffic forecast is fused into the BESS schedule. SCR increases by 8.4 percentage points because overnight grid charging is limited to what the forecast evening deficit requires, leaving battery headroom for the midday PV surplus; GDR falls by 3.9 points; and the mean daily evening peak falls by 10.9 kW (12.1%), because reserve energy is still available when the evening traffic peak arrives instead of having been used earlier in the peak-tariff window. From a distribution-network perspective, this reduces the coincident loading that the station imposes on the local feeder during the evening commute.

Two results qualify this benefit. First, waiting times are essentially unchanged: the high-traffic mean waiting time decreases by only 0.16 min (2.2%), and the all-day mean and 95th-percentile waiting times do not differ significantly. With peak class utilizations of 0.70 (DC) and 0.65 (Level-2), waiting is governed by the number of charge points relative to the arrival rate rather than by power availability, and curtailment ($LPSP \approx 1\%$) is too rare for the priority allocation to change throughput materially. Second, the daily energy cost increases slightly (+\$0.69, +0.9%), because TRLM holds its reserve by importing more during the afternoon peak-tariff hours; under the energy-only tariff of **Table 6**, the value of the peak reduction would have to be realized through a demand charge or a smaller grid connection, neither of which is modelled here.

The size of the benefit depends on forecast quality and on the evening energy deficit relative to battery capacity (Section VI-E), and the reported values are specific to the synthesized irradiance and traffic profiles, the sizing assumptions and the coefficient choices of this case study. Validation against field-measured traffic, session and irradiance data remains necessary (Section VII).

E. Queue Stability and Sensitivity to the Traffic-Sensitivity Coefficient

Using (18) with the charging model of Section V-B, the mean service times are 38.7 min (DC) and 106.6 min (Level-2), giving service capacities of 3.10 sessions/h for the two DC chargers and 2.25 sessions/h for the four Level-2 chargers (5.35 sessions/h in total). The mean peak arrival rate is 3.64 sessions/h ($TDI = 0.85$) and the largest possible rate is 4.0 sessions/h ($TDI = 1$), giving peak utilizations $\rho_{DC} = 0.70$ (0.77 at $TDI = 1$) and $\rho_{L2} = 0.65$ (0.71); the all-day averages are 0.47 and 0.43. All queues are therefore stable, and the waiting times in **Table 7** are measured values of a stable system. For comparison, a peak arrival rate of 15 sessions/h with 28 kWh per session would exceed the upper bound of $128.8/28 \approx 4.6$ sessions/h of a 128.8-kW station by a factor of more than three, and no finite steady-state waiting time would exist.

Table 8 repeats the comparison for $k_1 = 1.0$ and 2.0 ($R = 100$ days each, same seeding scheme). The evening peak reduction is largest when the evening energy deficit is small relative to the battery ($k_1 = 1.0$) and shrinks as traffic-driven demand grows; with $k_1 = 2.0$ the DC utilization at the evening peak reaches 0.84, the priority allocation begins to matter and the waiting-time and LPSP reductions become larger, while the cost penalty grows to 1.3%.

Table 8. Sensitivity of the paired differences (TRLM-baseline) to the traffic-sensitivity coefficient.

Quantity	$k_\alpha = 1.0$ ($R = 100$)	$k_\alpha = 1.5$ ($R = 300$)	$k_\alpha = 2.0$ ($R = 100$)
Peak arrival rate (TDI = 0.85); ρ_{DC}	2.96 sessions/h; 0.57	3.64 sessions/h; 0.70	4.31 sessions/h; 0.84
ΔSCR	+10.2 pp [9.6, 10.7]	+8.4 pp [7.9, 8.9]	+6.1 pp [5.3, 6.9]
ΔGDR	-5.2 pp [-5.7, -4.8]	-3.9 pp [-4.2, -3.7]	-2.7 pp [-3.0, -2.3]
Δ evening peak grid demand	-17.0 kW [-20.7, -13.4]	-10.9 kW [-12.5, -9.2]	-7.3 kW [-9.5, -5.0]
$\Delta LPSP$	+0.11 pp [-0.03, 0.25] (n.s.)	-0.11 pp [-0.19, -0.03]	-0.41 pp [-0.56, -0.25]
Δ waiting time (high traffic)	-0.01 min [-0.14, 0.12] (n.s.)	-0.16 min [-0.25, -0.07]	-0.31 min [-0.54, -0.08]
Δ daily energy cost	+\$0.18 [-0.38, 0.75] (n.s.)	+\$0.69 [0.32, 1.06]	+\$1.22 [0.66, 1.79]

Differences are mean [95% CI]; n.s.: not significant at the 5% level (paired t-test).

7. Conclusion and Future Work

A. Conclusion

This paper has presented the design and development of an electric vehicle charging station (EVCS) infrastructure integrated with a solar PV-based microgrid, in which charging power allocation is governed by a traffic-responsive load management (TRLM) strategy. A complete system architecture was proposed, comprising a PV array with MPPT, a battery energy storage system, a bidirectional grid-tied inverter, mixed Level-2/DC fast-charging points, and a traffic sensing layer feeding a centralized Energy Management System. Mathematical models were developed for the PV array (single-diode model with thermal derating), battery SOC dynamics, microgrid power balance, a Poisson-based traffic-responsive EV arrival model, and a priority-weighted charging power allocation algorithm incorporating a Traffic Density Index.

A Monte Carlo evaluation over 300 independent days, with common random numbers and a fully specified rule-based baseline operating under identical physical constraints, showed that the proposed TRLM strategy increases the PV self-consumption ratio by 8.4 percentage points, reduces the grid dependency ratio by 3.9 points and reduces the mean daily evening 15-min peak grid demand by 10.9 kW (12.1%), all statistically significant, while keeping the battery SOC within its 20% - 90% band. Waiting time was essentially unaffected (-0.16 min in high-traffic intervals), and daily energy cost increased by 0.9%. The anticipatory benefit derives from the traffic forecast; the few-minute lead time of an upstream detector supports only fast power allocation.

B. Limitations and Future Work

Several extensions to this work are recommended. First, the traffic, charging-session and irradiance profiles used in this study were synthetically generated and the arrival-model parameters are design assumptions; the calibration procedure of Section IV-D should be applied to field-measured detector data and charge-point session logs, together with site-specific irradiance measurements. Second, the rule-based planner does not trade peak reduction against energy cost, which

produced a small cost increase; a model-predictive formulation of (14) that includes demand charges and forecast uncertainty is a natural extension. Third, the priority weighting coefficients (α_1 , α_2 , α_3) were fixed; adaptive or learning-based tuning, for example using reinforcement learning, could be explored for varying seasonal and traffic conditions. Fourth, this paper analyzed the system at the power-flow/energy-management time scale; incorporating detailed converter switching dynamics, power quality analysis and protection coordination would support a more complete engineering design for field deployment. Finally, extending the framework to a network of traffic-responsive EVCS microgrid nodes, coordinated at the distribution-feeder or urban scale, is a promising direction for maximizing aggregate renewable utilization and peak demand reduction across a road network.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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List of Symbols

PV	Photovoltaic
$EVCS$	Electric Vehicle Charging Station
$BESS$	Battery Energy Storage System
EMS	Energy Management System
TDI	Traffic Density Index
$TRLM$	Traffic-Responsive Load Management
$MPPT$	Maximum Power Point Tracking
SOC	State of Charge
SCR	Self-Consumption Ratio
GDR	Grid Dependency Ratio
$LPSP$	Loss of Power Supply Probability
$G(t)$	Solar irradiance at time t (W/m^2)
$P_{pv}(t)$	PV array output power at time t (kW)
$P_{batt}(t)$	Battery charge/discharge power at time t (kW)
$P_{grid}(t)$	Power exchanged with the utility grid at time t (kW)
$\lambda(t)$	EV arrival rate at time t (vehicles/hour)
$\rho(t)$	Road traffic density at time t (vehicles/hour)
$N(t)$	Number of EVs present/charging at time t
$\tau_L(t)$	Traffic-observation-to-arrival lead time (min)
f_p	Pass-by capture fraction of passing vehicles that seek charging
η_c, η_d	One-way BESS charging and discharging efficiencies
$SOC_{res}(t)$	Planned reserve state of charge
P_{thr}	Planned grid peak-shaving threshold (kW)
ρ_k	Utilization of charger class k (L2 or DC)