



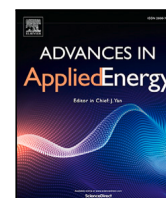
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Parishwad, O., Najafi, A., Yang, Y. et al (2026). User-redirection-aware co-optimization of public charging with local photovoltaics and battery storage. *Advances in Applied Energy*, 24. <http://dx.doi.org/10.1016/j.adapen.2026.100310>

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User-redirection-aware co-optimization of public charging with local photovoltaics and battery storage

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ARTICLE INFO

Dataset link: [repository](#)

Keywords:

Electric mobility
Charging solutions
Spatial user redirection
Photovoltaic with battery storage
Logic-based benders decomposition

ABSTRACT

Rapid transport electrification creates spatially concentrated and temporally varying charging demand, making public charging infrastructure a joint investment and localized energy management problem. This study develops a co-optimization approach, from a charging point operator perspective, integrating incentivized user redirection as a flexibility measure into the spatial joint deployment of multi-class public chargers and on-site solar photovoltaic generation, and battery energy storage, together with retail tariff-responsive grid procurement and battery operations. Logic-based Benders decomposition is used to separate infrastructure decisions from the discrete annual operational problem under user redirection, dynamic time-of-use tariffs, land use constraints, seasonal solar variability, and spatiotemporal charging demand. The method is tested in a case study in Gothenburg, Sweden, using multiple spatial, transport, and energy data sources. Relative to the chargers-only case without user redirection, the combined photovoltaic, battery storage, and user redirection case increases annual net profit by SEK 19.10 million (3.94%), reduces grid purchases by 32.77 GWh/year (28.4%), while serving all charging demand. Within the photovoltaic and storage configuration, user-redirection increases profit by SEK 1.73 million (0.34%), reduces the public charger count by 14.9%, and reallocates 2.08 GWh/year (2.10%) of public demand. The results indicate that local photovoltaics and battery storage account for most of the reduction in grid electricity use, while incentivized user redirection reduces the required chargers and improves the operational use of local energy and charging capacity, consequently amplifying the benefits of PV with battery storage.

1. Introduction

The rapid transition to electric mobility is turning urban charging infrastructure into a coupled transport and energy planning problem [1, 2]. Electric cars accounted for 28% of new car sales in Europe in 2025, and their share is expected to continue increasing as electrification progresses [3]. Despite rapid network expansion, public charging availability and capacity remain spatially uneven, while access to private charging also varies substantially across urban populations [3,4].

From an energy system perspective, public EV charging during peak hours introduces a rapidly growing and spatially concentrated electricity demand that must be served reliably and cost effectively. If unmanaged, this demand can increase peak grid purchases, exposure to high time-of-use (ToU) electricity prices, and contribute to localized network stress. Coupling charger planning with distributed energy resources and operational flexibility can mitigate these effects by reducing peak grid purchases and improving the local use of clean electricity [5,6]. In particular, on-site solar photovoltaic (PV) generation can supply part of charging demand locally, while battery energy

storage systems (BESS) provide temporal flexibility by shifting PV or grid electricity across operating periods [7,8]. Short-range spatial user redirection provides a complementary form of demand-side flexibility by reallocating charging demand among nearby stations and can address localized capacity mismatches that temporal shifting alone may not resolve [9,10]. Joint planning of charging infrastructure with PV and BESS is receiving increasing attention, but its interaction with endogenous spatial user redirection in long-term planning remains underexplored. Recent city-scale work has advanced demand-driven charging capacity planning [11], while transport-aware models have begun to co-plan charging infrastructure with PV and energy storage [12]. However, these planning frameworks do not examine how incentivized user redirection changes long-term decisions on multi-type charger deployment, PV and BESS investment, grid procurement, and PV electricity used locally.

To address these gaps, this study makes three key contributions:

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Nomenclature

A. Sets and indices:

$b \in \mathcal{B}$	Demand classes, $\mathcal{B} = \{\text{home, public}\}$.
$c, c^o, c^d \in \mathcal{C}$	Public charger types $\{\text{slow, medium, fast}\}$. c^o and c^d denote the origin reference type and destination service type, for redirected public charging demand.
$i, j \in \mathcal{I}$	Hexagonal planning zones. Index i generally denotes an origin or local zone, while j denotes a candidate redirection destination.
$m \in \mathcal{M}$	Months.
$t \in \mathcal{H}$	Operational intervals within a representative day, $\mathcal{H} = \{1, 2, \dots, 48\}$.
$\ell \in \mathcal{H}_0$	BESS energy-state boundary indices, $\mathcal{H}_0 = \{0\} \cup \mathcal{H} = \{0, 1, \dots, 48\}$.
$(i, j) \in \mathcal{D}$	Candidate redirection arcs with shortest-path distance $d_{ij} \leq d_{\max}$.
$(i, j, m, t) \in \mathcal{A}$	Active tuples, $\mathcal{A} \subseteq \mathcal{D} \times \mathcal{M} \times \mathcal{H}$, retained after baseline demand filtering in slot (m, t) .
$\mathcal{A}_{m,t}$	Active arcs in slot (m, t) : $\mathcal{A}_{m,t} := \{(i, j) \in \mathcal{D} : (i, j, m, t) \in \mathcal{A}\}$.
$q \in \mathcal{Q}_{m,t}$	Connected-component index of the eligible user redirection graph in slot (m, t) .
$\mathcal{I}_{m,t,q}, \mathcal{A}_{m,t,q}$	Zones and active arcs, in component $q \in \mathcal{Q}_{m,t}$.

B. Input parameters:

$\sigma^{\text{init}}, \underline{\sigma}, \bar{\sigma}$	Initial, minimum, and maximum BESS SoC fractions.
$\eta_{\text{ch}}, \eta_{\text{dis}}$	BESS charging and discharging efficiencies.
M_i^{batt}	Constant site-level big- M used for BESS charge/discharge mode exclusivity.
$\kappa, \kappa_{\min}$	Nominal energy per redirected trip and minimum redirected energy required to activate an arc, respectively (kWh).
c^{slack}	Penalty cost for unmet charging demand (SEK/kWh).
c^{detour}	Generalized detour time compensation coefficient (SEK/km).
$T_{i,j}, \gamma_{i,j}$	Per-trip and equivalent per kWh user redirection incentives, with $\gamma_{i,j} = T_{i,j}/\kappa$.
$v_{\text{car}}, v_{\text{walk}}$	Driving, walking speed (km/h).
v_{time}	Value of time (SEK/h).
$D_{i,m,t,b}$	Optimization-ready charging demand at zone i in slot (m, t) for class b (kWh/interval). For $b = \text{home}$, this denotes residual home demand after accounting for exogenous private home charging capacity.
$N_m^{\text{days}}, N_{\text{days}}^{\text{yr}}$	Number of representative days in month m and total number of days in the annual planning horizon, with $\sum_{m \in \mathcal{M}} N_m^{\text{days}} = N_{\text{days}}^{\text{yr}}$.
$\bar{N}_i^{\text{PV}}, \bar{B}_i$	Maximum installable PV panels and BESS units at zone i .
$\text{Cap}^{\text{batt}}, K^{\text{batt}}$	Energy capacity and maximum per-interval charge/discharge energy of one BESS unit.
$\bar{C}_i^{\text{pub}}, a_c^{\text{chg}}$	Available installation resource at zone i and requirement of one charger of type c .

K_c, K^{PV}	Per-interval energy capacity (kWh/interval) of charger type c (K_c) or PV panel (K^{PV}).
$l_c, l_{\text{PV}}, l_{\text{batt}}$	Upfront unit costs of public chargers, PV panels, and BESS units, respectively.
ϖ_c	Charging tariff for public charger type c (SEK/kWh).
$\Delta_{c^o, c^d}^{\text{price}}$	Per kWh charging tariff compensation coefficient for user redirection from origin charger type c^o to destination charger type c^d , as the nonnegative tariff difference.
$\rho_{m,t}$	Retail grid electricity price in slot (m, t) (SEK/kWh).
$\text{PVF}_g(r, n_g)$	Daily capital-recovery factor for asset class g (day^{-1}), computed from annual discount rate r and lifetime n_g years.
$f_{m,t}^{\text{PV}}$	Dimensionless PV capacity factor in slot (m, t) .
$d_{\max}, D_{\min}^{\text{arc}}$	Distance and baseline demand thresholds defining candidate and user redirection arcs.
d_{ij}	Road-network shortest-path distance between planning zones i and j (km).
M_j^{redir}	Valid upper bound for the type aggregated redirected energy $z_{i,j,m,t}$ on an arc terminating at zone j (kWh/interval).

C. Decision variables:

$x_{i,c} \in \mathbb{Z}_+$	Installed public chargers of type c at zone i .
$N_i^{\text{PV}}, B_i \in \mathbb{Z}_+$	Installed PV panels and BESS units at zone i .
$d_{i,m,t}^{\text{dis}} \geq 0$	Site-level BESS discharge to the public-charging bus (kWh/interval).
$\chi_{i,m,\ell} \geq 0$	Stored BESS energy at boundary index ℓ in month m and zone i (kWh).
$\delta_{i,m,t} \in \{0, 1\}$	Binary charging/discharging mode indicator.
$e_{i,m,t,b} \geq 0$	Unserved demand for class b (kWh/interval).
$e_{i,m,t,c,b} \geq 0$	Energy delivered by public charger type c to demand class b (kWh/interval).
$g_{i,m,t}^{\text{batt}}, p_{i,m,t}^{\text{batt}} \geq 0$	Grid and PV energy routed to BESS charging (kWh/interval).
$g_{i,m,t}^{\text{dir}}, p_{i,m,t}^{\text{dir}} \geq 0$	Grid and PV energy supplied directly to charging load.
$w_{i,m,t,c}^{\text{orig}} \geq 0$	Baseline public charging demand assigned to origin reference charger type c (kWh/interval).
$n_{i,j,m,t}^{\text{full}} \in \mathbb{Z}_+$	Number of complete κ -sized redirected-trip bundles on arc (i, j) in slot (m, t) .
$u_{i,j,m,t}^{\text{tail}} \geq 0$	Residual redirected energy below one nominal trip quantum on arc (i, j) in slot (m, t) (kWh/interval).
$Y_{i,j,m,t} \in \{0, 1\}$	Binary indicator of whether user redirection arc (i, j) is activated in slot (m, t) .
$z_{i,j,m,t} \geq 0$	Aggregate public charging energy redirected on arc (i, j) in slot (m, t) .
$z_{i,j,m,t,c^o,c^d} \geq 0$	Type-pair redirected energy with origin reference type c^o and destination service type c^d .

D. LBBD-specific notation:

$\xi \in \mathcal{X}$	Infrastructure vector and its feasible set.
$\mathcal{Y}(\xi), \hat{\mathcal{Y}}(\xi)$	Exact annual operational feasible set and embedded master relaxation under infrastructure ξ .
$\eta \in \mathbb{R}$	Master upper approximation of total annual CPO profit.
$\theta_{m,t,q} \in \mathbb{R}$	Component-slot upper approximation of grid baseline operating profit.
$\phi^{\text{LP}}(\xi), \phi^{\text{MIP}}(\xi)$	Optimal complete annual profit values of the linked annual LP relaxation and exact annual MIP, under fixed infrastructure ξ .
$\bar{\xi}^{(k)}, \xi^{o,(k)}$	Infrastructure candidate at iteration k and the corresponding running, potentially fractional, core point.
$\text{UB}^{(k)}, \text{LB}^{(k)}$	Global upper bound and certified global feasible lower bound at iteration k , respectively.
$k, \text{Gap}^{(k)}$	Certified relative LBBD gap at LBBD iteration index k .
$\epsilon_{\text{LBBD}}, \epsilon_k^{\text{MP}}$	LBBD termination tolerance and set master-solver MIP gap.
$Z^k, \bar{Z}^k$	Feasible exact annual MIP objective value and solver best bound for the infrastructure configuration evaluated at iteration k .
$\bar{\eta}$	Valid global upper cap on annual CPO profit used in the LBBD master.
ω	Running-core-point update weight used for the additional annual LP evaluation.
$\epsilon_{\min}^{\text{MP}}, \rho_{\text{MP}}$	Minimum requested master MIP gap and multiplicative master-gap tightening factor.

- A joint planning formulation: We integrate user-incentive redirection with charging infrastructure and local energy system planning within a single optimization model, so that the redirection of users is a decision variable of the planning problem rather than an exogenous input.
- Quantification of the resulting effects: We quantify how incentive-based redirection affects infrastructure requirements, energy procurement and use, compensation costs, and charge point operator (CPO) profit, making the trade-offs between these quantities explicit.
- A tractable solution method: User incentivized redirection introduces many discrete trip, arc activation, and charger-type assignment variables into the optimization. We therefore develop, implement, and validate a logic-based Benders decomposition (LBBD) approach, and demonstrate its ability to solve large-scale instances of the problem.

We formulate the problem as an operator-side optimization that maximizes annual CPO profit by jointly determining infrastructure siting and sizing for multi-type chargers, PV, and BESS; spatial user redirection through incentives; and the operational decisions on grid electricity procurement and BESS dispatch. The formulation captures road network-based redirection feasibility and incentive compensation, retail tariff-responsive grid procurement and BESS scheduling, monthly variation in PV availability, and land use based siting bounds. Spatiotemporal charging demand is obtained at half-hour resolution from the behaviorally grounded activity-based simulation framework developed in [13]. The complete operational problem retains discrete decisions associated with user redirection, for which classical Benders

decomposition based on LP subproblem duality is not directly applicable under the adopted decomposition. We therefore formulate the planning problem as an MILP and solve it using logic-based Benders decomposition (LBBD), which separates strategic infrastructure decisions from complete annual operational evaluations. The approach is applied to a case study of the Greater Gothenburg area, accounting for monthly representative days, a half-hour temporal resolution, month-specific PV and tariff profiles, land use-based installation limits, and a road network compiled from multiple data sources.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on EV charging infrastructure planning, renewable integration, demand-side flexibility, and scalable optimization, and positions the contribution of this study. Section 3 presents the problem setting, modeling assumptions and mathematical formulation, and Section 4 describes the decomposition-based solution methodology. Section 5 presents the Gothenburg case study, while Section 6 reports the numerical results, sensitivity analyses, and computational performance. Finally, Section 7 concludes and outlines limitations and future research.

2. Literature review

Urban EV charging infrastructure planning has moved from a facility location problem toward a coupled transport and energy planning problem. Recent reviews highlight the increasing importance of spatiotemporal charging demand, transport–energy interactions, distributed energy resources, and integrated planning and operation [2, 14–16].

2.1. Demand modeling for infrastructure planning

A central challenge in charging infrastructure planning is the representation of charging demand. Early studies often used crude assumptions such as population, traffic counts, land use, or points of interest. These inputs are useful for strategic screening, but they can understate the spatiotemporal concentration and intraday peaks that drive charger capacity, electricity costs, and storage value [14,17]. More recent work has therefore used mobility traces, travel surveys, observed charging behavior, activity-based models, and agent-based simulations to preserve the spatial and temporal heterogeneity of charging demand [6, 13,18]. This shift is important because PV output, retail tariffs, and BESS operation depend strongly on when and where charging occurs. Planning models that preserve time of day and spatial heterogeneity can therefore evaluate local renewable use and storage dispatch more realistically than models based only on annual energy totals [19,20]. This study uses charging events from the behaviorally grounded MAT-Sim simulation [13], which represents cost-aware charger selection and feasible rescheduling under activity and battery constraints. Aggregation to hexagonal-grid planning zones and half-hour intervals retains spatiotemporal variation while limiting optimization size.

2.2. Public charger siting and sizing

Charging infrastructure siting and sizing studies have traditionally focused on coverage, accessibility, utilization and investment cost. Network based and rule based approaches improved spatial realism by using road networks, mobility patterns, and candidate facility sets [21, 22]. Later studies incorporated spatiotemporal demand, heterogeneous charger types, and service quality requirements [14,23]. These studies provide important foundations for public charging deployment, but many still treat charging primarily as a transport accessibility asset. A growing stream of studies links charging infrastructure planning with power system or grid constraints. Some models explicitly include distribution network limits, power-flow approximations, or hosting-capacity constraints in charging infrastructure planning [24–26]. These studies show that electrical constraints can reshape siting decisions. They also require detailed grid network data that may not be available to a CPO at city scale.

Table 1
Synthesis of related studies and positioning of this study.

Reference	Year	Infrastructure planning	City scale	PV	BESS	Retail tariff	Spatial charging flexibility	Behavior-informed demand	Decomposition	Grid model
[27]	2022	–	–	✓	✓	✓	–	–	–	–
[18]	2023	✓	–	–	–	–	–	✓	–	–
[7]	2023	✓	–	✓	✓	✓	–	–	✓	–
[29]	2023	–	–	✓	✓	✓	–	–	–	–
[5]	2023	–	–	✓	✓	✓	–	–	–	–
[30]	2023	–	–	–	–	✓	✓	✓	✓	–
[31]	2024	✓	✓	–	–	–	–	–	–	–
[8]	2024	✓	✓	✓	✓	✓	–	–	–	–
[32]	2024	✓	–	–	–	✓	–	–	–	–
[20]	2024	–	–	–	–	✓	✓	–	–	–
[26]	2024	✓	–	–	–	–	–	–	–	✓
[10]	2024	–	–	–	–	–	✓	✓	–	–
[6]	2024	✓	–	✓	✓	✓	–	✓	–	–
[33]	2025	–	✓	–	–	✓	–	✓	–	–
[24]	2025	✓	–	✓	–	✓	–	–	–	✓
[34]	2025	✓	–	✓	✓	✓	–	–	–	–
[35]	2025	✓	–	–	–	–	–	–	✓	–
[36]	2025	✓	✓	–	–	–	–	–	✓	–
[37]	2025	✓	✓	–	–	–	–	–	✓	–
[9]	2025	–	–	–	–	–	✓	✓	–	–
[25]	2025	✓	✓	–	–	–	–	–	–	✓
[13]	2026	–	✓	–	–	✓	–	✓	–	–
[11]	2026	✓	✓	–	–	–	–	–	–	–
[28]	2026	–	–	✓	✓	✓	✓	–	–	–
[12]	2026	✓	–	✓	✓	–	–	–	–	✓
This study	–	✓	✓	✓	✓	✓	✓	✓	✓	–

Note: A checkmark indicates that the feature is explicitly modeled, used, or quantitatively analyzed rather than discussed only as context. *Grid model* denotes explicit distribution-network, power flow, hosting capacity, or equivalent network constraints.

2.3. PV and BESS enabled charging operations

PV and BESS have been shown to reduce grid dependence and shift charging energy across time in station, fleet, depot, and integrated energy settings [6–8]. Large-scale public transport studies show that coordinated PV and storage operation can reduce charging-related grid loads, while integrated local energy studies demonstrate that charging behavior affects the value of locally available solar electricity [6,8]. More recent transport-aware planning models have begun to jointly optimize charging infrastructure, PV, and energy storage [12]. Two recent electric bus studies provide complementary evidence at the operational scale. A rolling-horizon campus study used measured PV-generation and bus-operation data while accounting for uncertainty in PV output and bus arrival times. The optimized schedule reduced monthly operating cost by 52% relative to the observed campus schedule [27]. A separate MILP study coordinated charging times, charging locations, and station-level energy allocation for a fleet of 128 buses supplied by 18 PV–storage–charging stations under temperature and solar conditions in six Chinese cities. The reported annual operating-cost reductions were 10%–15% [28]. These studies establish the importance of jointly considering charging infrastructure and local energy resources. However, incentivized spatial user redirection is generally not represented as endogenous operational recourse within long-term public charging infrastructure planning. This distinction is relevant because changing where demand is served can alter charger utilization, PV electricity used locally, storage requirements, and the economic value of individual charging sites.

2.4. Demand side flexibility and spatial redirection

Demand-side flexibility in EV charging is typically discussed in terms of temporal and spatial shifts. Temporal flexibility includes managed charging, price response, delayed charging, and aggregator control. Studies show that such flexibility depends on user acceptance, perceived inconvenience, control preferences, and incentive design [38–40]. However, in planning models, these behavioral dimensions are often simplified to preserve tractability.

Spatial redirection is a complementary mechanism that reallocates part of public charging demand among nearby locations rather than shifting charging only in time. Recent studies quantify spatial charging flexibility through price-responsive station choice and route-station interactions under user choice uncertainty [9,10]. Related incentive-aware routing formulations show that monetary compensation can be incorporated into joint routing and charging decisions [30], while stochastic demand-response formulations emphasize the importance of uncertainty and heterogeneous user response [32]. These mechanisms are related to, but not identical to, the incentivized user redirection recourse considered in this study. Most studies of spatial charging flexibility are operational in nature. They generally examine charging-location choice, routing, pricing, or incentive response without embedding incentivized user redirection as recourse within long-term planning of public chargers, PV, and BESS. Accordingly, the formulation contribution lies in treating the service location of eligible public-destination demand as an endogenous operational decision coupled to long-term investment in chargers, PV, and BESS and to their annual operation, rather than in any individual model component. Once demand can be redirected, the value of a charging site depends not only on its local baseline demand but also on whether nearby demand can be served there at lower cost.

2.5. Scalable optimization for integrated charging planning

Joint optimization of public charger deployment, user redirection, PV and BESS sizing, and temporally resolved BESS operation yields a large mixed-integer problem whose dimensions grow with the number of planning sites, time intervals, charger classes, and feasible redirection links. The monolithic solution can therefore become computationally demanding at city scale. Benders-type decomposition has been applied to large charging-infrastructure expansion and location-routing problems to exploit separable structure and reduce computational burden [35,36]. Logic-based Benders decomposition is particularly relevant when fixed strategic decisions leave discrete or combinatorial operational recourse. Recent bus-fleet electrification planning provides an application with integer operational subproblems [37]. Complementary vehicle operation research evaluates electric bus life-cycle

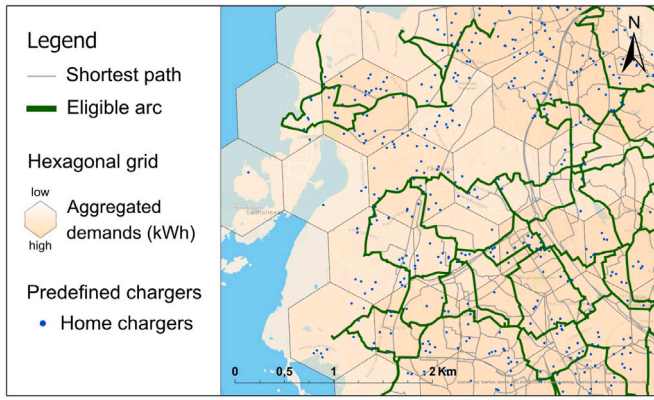


Fig. 1. Preprocessing of charging demand and eligible user-redirection arcs.

emissions from field data and optimizes driving speed on dynamic wireless charging lanes. These studies address distinct operating decisions within the broader transport-energy system [41,42].

Table 1 summarizes representative studies across the principal strands of the literature. The comparison considers whether each study explicitly models, uses, or quantitatively analyzes charging infrastructure planning, city-scale applications, PV and BESS, retail electricity tariffs, spatial charging flexibility, behavior-informed demand, decomposition methods, and distribution grid constraints. Spatial charging flexibility is used here as a broad category covering endogenous charging location choice, routing-based charging allocation, and spatial demand redistribution, whereas the present study specifically represents incentivized user redirection. Overall, city-scale infrastructure planning, local PV and BESS integration, behavior-informed charging demand, spatial flexibility, and scalable decomposition methods are generally addressed in different formulations. The present study focuses on their intersection by endogenizing user redirection within CPO-side planning of multi-type public chargers, PV, and BESS while retaining temporally resolved operation and behaviorally grounded charging demand.

3. Problem description and modeling

This section formulates the planning problem from the perspective of a charging-point operator (CPO) that invests in and operates public EV chargers, on-site PV, and BESS. The model determines long-term infrastructure decisions, including the number and type of public chargers, PV panels, and BESS units installed in each planning zone, together with operational decisions for incentivized user redirection, grid electricity procurement, PV utilization, and BESS dispatch. We first define the system boundary, demand preprocessing, and main modeling assumptions, and then present the objective function and constraints used in the optimization framework (Fig. 2).

3.1. Problem description

The CPO jointly selects public chargers, PV, and BESS and operates these assets through grid procurement, storage dispatch, and incentivized user redirection. Spatiotemporal charging demand is a fixed exogenous input from the preceding activity-based simulation [13]. The objective maximizes annual CPO profit under fixed charger-type tariffs, siting bounds, and an explicitly penalized unmet-demand slack. Charger-type tariffs apply uniformly to modeled users. The formulation represents commercial CPO planning rather than a municipal social-welfare, equity, or universal-coverage objective. Municipal implementation would require separate access, land, permitting, and grid-feasibility assessment.

To obtain optimization-ready charging demand inputs, simulated charging events (charging time window and required energy of each event) are aggregated spatially to hexagonal planning zones and temporally to fixed half-hour slots. The spatial and half-hour aggregation supports strategic capacity planning while aligning charging demand, PV availability, tariffs, and BESS operation. Final parcel selection remains outside the model scope. The zones represent planning zones, rather than parcel-level installation sites.

Private home chargers are exogenous and are not optimized. Demand satisfied by these chargers is removed during preprocessing and excluded from CPO investment, energy, cost, and revenue accounting. Residual home demand is restricted to local public charger service, except for penalized unmet-demand slack, while work and other public-destination demand may be redirected between eligible zones. Public chargers, PV, and BESS are selected within zone-specific siting bounds. Grid imports, direct PV use, and BESS discharge supply CPO-served demand. PV export is excluded. Feeder, transformer, voltage, power flow, hosting capacity, and grid reinforcement constraints are outside the scope of this formulation.

Short-range user redirection is modeled as localized spatial flexibility for public charging demand. A portion of public demand in an origin zone may be served at a nearby destination zone if an eligible road-network connection exists and the destination has available charging capacity or more favorable operating conditions. Eligible redirection arcs are constructed from existing road network shortest-path routes between zone centroids, as illustrated in Fig. 1. The CPO compensates the modeled detour and any positive tariff difference between the origin reference type and destination service type. The model does not estimate individual acceptance probabilities. Eligible compensated user-redirections are treated as behaviorally admissible under the scenario assumptions. Seasonal variability is represented through month-specific ToU tariffs and PV availability profiles, while charging demand is represented by one aggregated representative day that is repeated across months and scaled by N_m^{days} [43,44]. Thus, $D_{i,m,t,b} = D_{i,t,b}$ for all $m \in \mathcal{M}$, whereas $\rho_{m,t}$ and $f_{m,t}^{\text{PV}}$ remain month dependent. This aggregation reduces computational burden while retaining the tariff and solar-resource variation most relevant for PV and BESS investment and operation. The resulting limitation is that seasonal and day-to-day variation in charging demand is not represented explicitly. The objective is to maximize annual profit by balancing charging revenue against grid procurement costs, redirection incentives, unmet-demand penalties, and annualized investment costs. Fig. 2 summarizes the investment, operational, and economic relationships represented in the model. The following subsections present the optimization formulations that define the planning problem. Section 4 then describes the deployed decomposition approach to solve the optimization problem. The principal sets, input parameters, and decision variables are summarized in the nomenclature.

3.2. Objective function

The mixed-integer linear program (MILP) maximizes annual profit from the CPO perspective by combining infrastructure investment and public charging operation. The operating terms include charging revenue, grid electricity procurement cost, user redirection incentive payouts, and penalties for unmet demand, while the investment terms represent the annualized capital costs of public chargers, PV, and BESS. Because public charging tariffs are fixed by charger type, total charging revenue changes only when the served energy volume, unmet demand, or charger type allocation changes. Each month m is represented by a typical day. The operating cash flows are computed over that representative day and scaled by N_m^{days} , while daily annuity-equivalent infrastructure investment costs are scaled by $N_{\text{days}}^{\text{yr}}$ to obtain annual values. This distinction is intentional. Operating terms vary across months because PV availability and electricity tariffs are

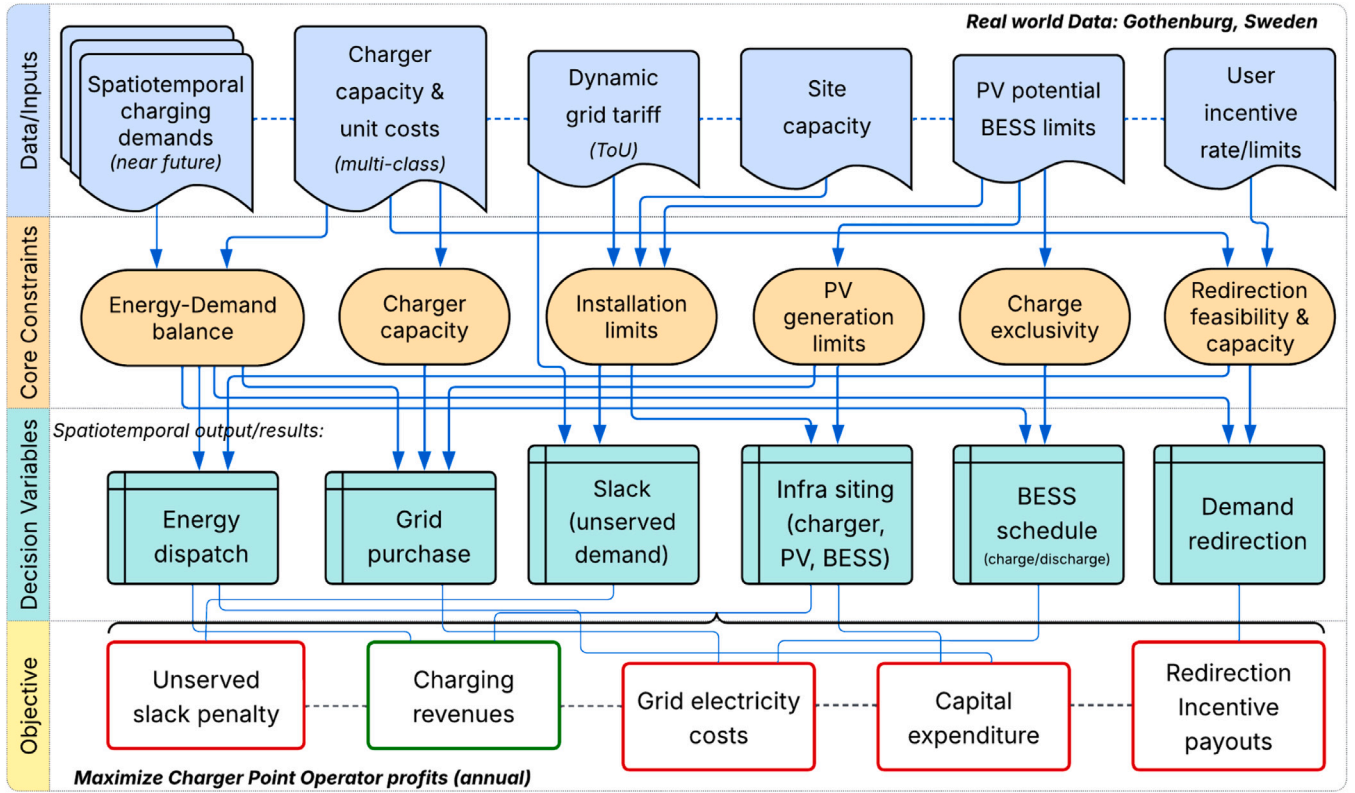


Fig. 2. Optimization framework: data inputs, decision layers, coupling constraints, and annual profit components.

month specific, whereas infrastructure investments are long term planning decisions and are therefore annualized independently of monthly operating conditions.

$$\max_{m \in \mathcal{M}} \sum_{m \in \mathcal{M}} N_m^{\text{days}} \left(\text{Revenue}_m - \text{Cost}_m^{\text{grid}} - \text{Cost}_m^{\text{incentive}} - \text{Cost}_m^{\text{slack}} \right) - N_{\text{days}}^{\text{yr}} \left(\text{CapEx}^{\text{chargers}} + \text{CapEx}^{\text{PV}} + \text{CapEx}^{\text{BESS}} \right). \quad (1)$$

Here, Revenue_m , $\text{Cost}_m^{\text{grid}}$, $\text{Cost}_m^{\text{incentive}}$, and $\text{Cost}_m^{\text{slack}}$ denote the month-specific representative day operating cash flows in month m (defined in Eqs. (2)–(7)). The terms $\text{CapEx}^{\text{chargers}}$, CapEx^{PV} , and $\text{CapEx}^{\text{BESS}}$ denote daily annuity equivalent investment costs obtained by applying the capital recovery factors in Eq. (8) to the corresponding upfront unit costs. Multiplication by $N_{\text{days}}^{\text{yr}}$ converts these terms into annualized investment costs.

- **Charging revenue** (Revenue_m) is earned only on energy delivered by public chargers and is billed at charger type-specific tariffs. This includes public charger service to baseline public demand, incoming redirected public demand, and residual home demand served through public infrastructure. Charging served by private home chargers remains outside the CPO boundary and is not included in revenue.

$$\text{Revenue}_m = \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{H}} \sum_{b \in \mathcal{B}} \sum_{c \in \mathcal{C}} \varpi_c e_{i,m,t,c,b}. \quad (2)$$

Here, $e_{i,m,t,c,b}$ represents energy served by public charger type c to demand class b at zone i after any user redirection has been accounted for in the demand balance.

- **Grid electricity procurement cost** ($\text{Cost}_m^{\text{grid}}$) captures both electricity purchased for immediate charging service and electricity

purchased to charge the BESS for later use.

$$\text{Cost}_m^{\text{grid}} = \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{H}} \rho_{m,t} \left(g_{i,m,t}^{\text{dir}} + g_{i,m,t}^{\text{batt}} \right). \quad (3)$$

Here, $g_{i,m,t}^{\text{dir}}$ denotes grid energy supplied directly to the public chargers, while $g_{i,m,t}^{\text{batt}}$ denotes grid energy routed to battery charging, with both charged at the month- and interval-specific ToU tariff $\rho_{m,t}$.

- **User-redirection incentives** ($\text{Cost}_m^{\text{incentive}}$) compensate users for the generalized disutility of a short detour and for any positive charging tariff difference when redirected demand is served by a costlier destination charger type. To preserve interpretability, redirected energy is modeled at the trip level using a nominal energy-per-trip quantum κ , with a pro-rata tail that preserves continuity when redirected energy is not an exact multiple of κ . The tariff-compensation coefficient for user redirection from the origin charger type c^o to destination charger type c^d is defined as $\Delta_{c^o,c^d}^{\text{price}}$ in Eq. (4).

$$\Delta_{c^o,c^d}^{\text{price}} = \max \{0, \varpi_{c^d} - \varpi_{c^o}\}, \quad \forall c^o, c^d \in \mathcal{C}. \quad (4)$$

Let $z_{i,j,m,t}$ denote the aggregate redirected public charging energy on physical arc (i, j) in slot (m, t) .

$$z_{i,j,m,t} = \sum_{c^o \in \mathcal{C}} \sum_{c^d \in \mathcal{C}} z_{i,j,m,t,c^o,c^d}, \quad \forall (i, j, m, t) \in \mathcal{A}. \quad (5)$$

The monthly representative day user-redirection incentive cost is then defined as follows.

$$\begin{aligned} \text{Cost}_m^{\text{incentive}} = & \sum_{i \in \mathcal{H}} \sum_{(i,j) \in \mathcal{A}_{m,t}} \left(T_{i,j} n_{i,j,m,t}^{\text{full}} + \gamma_{i,j} u_{i,j,m,t}^{\text{tail}} \right) \\ & + \sum_{i \in \mathcal{H}} \sum_{(i,j) \in \mathcal{A}_{m,t}} \sum_{c^o \in \mathcal{C}} \sum_{c^d \in \mathcal{C}} \Delta_{c^o,c^d}^{\text{price}} z_{i,j,m,t,c^o,c^d}. \end{aligned} \quad (6)$$

The aggregate variable $z_{i,j,m,t}$ is used for trip level incentive accounting and is linked to the full charger type pair tensor through Eq. (5). The trip bundle constraints are stated in Section 3.6.

In Eq. (6), the first term compensates whole redirected trips and the associated residual redirected energy. Defining $\gamma_{i,j} := T_{i,j}/\kappa$ gives a per kWh representation for the tail component. The second term compensates only the positive tariff difference between the destination charger type c^d and the origin charger type c^o assigned to the redirected public charging energy. Thus, user redirection to a costlier charger type is not prohibited, but it becomes less profitable through the additional compensation term.

- **Slack penalty** ($\text{Cost}_m^{\text{slack}}$) heavily penalizes unmet charging demand and is included to discourage demand shedding except where unavoidable.

$$\text{Cost}_m^{\text{slack}} = c^{\text{slack}} \sum_{i \in I} \sum_{t \in H} \sum_{b \in B} e_{i,m,t,b}. \quad (7)$$

The coefficient c^{slack} is chosen sufficiently large to enforce near-complete demand satisfaction in normal conditions, while retaining model feasibility in cases of extreme local scarcity or binding infrastructure limits.

The *annualized infrastructure capital expenditure (CapEx)* terms convert upfront infrastructure investment costs into equivalent daily annuity costs using the factors PVF_g . For each asset class $g \in \{\text{slow, medium, fast, PV, BESS}\}$, the factor $\text{PVF}_g(r, n_g)$ acts as a daily capital-recovery factor that maps an upfront unit cost into a daily annuity equivalent cost using discount rate r and asset lifetime n_g .

$$\text{PVF}_g = \frac{1}{365} \frac{r(1+r)^{n_g}}{(1+r)^{n_g} - 1}. \quad (8)$$

These daily recovery factors are then multiplied by the corresponding installed asset quantities to obtain the daily annuity equivalent investment costs for chargers, PV, and BESS.

$$\text{CapEx}^{\text{chargers}} = \sum_{i \in I} \sum_{c \in C} \text{PVF}_c \cdot t_c \cdot x_{i,c}, \quad (9)$$

$$\text{CapEx}^{\text{PV}} = \sum_{i \in I} \text{PVF}_{\text{PV}} \cdot t_{\text{PV}} \cdot N_i^{\text{PV}}, \quad (10)$$

$$\text{CapEx}^{\text{BESS}} = \sum_{i \in I} \text{PVF}_{\text{BESS}} \cdot t_{\text{batt}} \cdot B_i. \quad (11)$$

Together, these terms internalize the CPO's economic trade-off between serving spatiotemporal charging demand, procuring and shifting electricity through grid and PV and BESS resources, compensating acceptable short range user redirection, and investing in the charging and energy infrastructure.

3.3. Charging infrastructure and charging demand fulfillment

This subsection describes how public charger deployment is linked to the fulfillment of spatiotemporal charging demand. It defines the installation limits and service capacities of public chargers, and then formalizes how charging demand is covered within the CPO-operated charging system, including the treatment of unmet demand through penalized slack variables.

Public charger installation upper bounds. Land-use and parking-availability constraints define a site-level installation resource budget for public charging infrastructure in each zone $i \in I$.

$$\sum_{c \in C} a_c^{\text{chg}} x_{i,c} \leq \bar{C}_i^{\text{pub}}, \quad \forall i \in I. \quad (12)$$

Here, $x_{i,c}$ denotes the integer number of installed public chargers of type c , a_c^{chg} denotes the installation resource coefficient of charger type c , and $\bar{C}_i^{\text{pub}}$ denotes the available charger installation resource in zone i .

Charging capacity. Each public charger of type c can deliver up to K_c kWh per half-hour interval. Accordingly, for every zone, month, interval, and charger type, the total energy delivered by installed chargers cannot exceed the available installed charging capacity.

$$\sum_{b \in B} e_{i,m,t,c,b} \leq K_c x_{i,c} \quad (13)$$

$$\forall i \in I, m \in \mathcal{M}, t \in H, c \in C.$$

The variable $e_{i,m,t,c,b}$ denotes the energy delivered by public charger type c to demand class b in zone i and slot (m, t) .

Demand coverage and slack variables. Private home charging lies outside the CPO investment and operating boundary. Preprocessing subtracts the lesser of baseline home demand and available private charging capacity in each zone and interval. The remainder, $D_{i,m,t,\text{home}}$, is restricted to local public-charger service except for the explicitly penalized slack in Eq. (14). The separate class $D_{i,m,t,\text{public}}$ combines work and other public-destination demand.

$$\sum_{c \in C} e_{i,m,t,c,\text{home}} + e_{i,m,t,\text{home}} = D_{i,m,t,\text{home}}, \quad (14)$$

$$\forall i \in I, m \in \mathcal{M}, t \in H.$$

Residual home demand is not eligible for spatial redirection and must therefore be served by public chargers in its origin zone locally, or represented through $e_{i,m,t,\text{home}}$.

In the formulation, public charging demand in a zone is satisfied after accounting for outgoing and incoming redirected demand. The effective public demand served in a zone therefore equals its baseline public demand minus demand sent to other zones plus demand received from neighboring zones. User-redirection is indexed by both the origin charger type c^o and the destination charger type c^d so that the optimization can identify the charger-type pairing associated with each redirected public charging flow.

$$\sum_{c \in C} e_{i,m,t,c,\text{public}} + e_{i,m,t,\text{public}} = D_{i,m,t,\text{public}} - \sum_{j:(i,j,m,t) \in A} z_{i,j,m,t} + \sum_{j:(j,i,m,t) \in A} z_{j,i,m,t}, \quad (15)$$

$$\forall i \in I, m \in \mathcal{M}, t \in H.$$

Here, $z_{i,j,m,t}$ denotes aggregate redirected public charging energy on physical arc (i, j) , as defined in Eq. (5). Thus, outgoing redirected energy decreases the effective public demand served in the origin zone, while incoming redirected energy increases the effective public demand served in the destination zone. The charger-type-pair tensor z_{i,j,m,t,c^o,c^d} preserves the origin tariff-reference type c^o and the physical destination service type c^d .

Outgoing user redirection from an origin zone cannot exceed the baseline public demand available in that zone and slot.

$$\sum_{j:(i,j,m,t) \in A} z_{i,j,m,t} \leq D_{i,m,t,\text{public}}, \quad (16)$$

$$\forall i \in I, m \in \mathcal{M}, t \in H.$$

Nonnegative slack $e_{i,m,t,b}$ records unmet demand and incurs the penalty c^{slack} . This retains feasibility under binding infrastructure limits without treating demand shedding as costless.

3.4. Energy supply and renewable integration

This subsection defines the site-level energy supply balance. It ensures that all energy delivered by public chargers is supplied by one of three sources (grid electricity, on-site PV generation, or BESS discharge), and that PV utilization remains within the generation potential implied by installed PV capacity and varying solar availability.

Energy supply for satisfying charging demand. For each zone $i \in \mathcal{I}$, month $m \in \mathcal{M}$, and interval $t \in \mathcal{H}$, total energy supplied to the public charging system must equal total energy delivered by public chargers. Supply is represented at the site interval level through grid procurement, direct PV use, and BESS discharge, whereas the delivered energy variables are partitioned by demand class $b \in \{\text{home}, \text{public}\}$ to distinguish service to residual home demand from service to public charging demand.

$$g_{i,m,t}^{\text{dir}} + p_{i,m,t}^{\text{dir}} + d_{i,m,t}^{\text{dis}} = \sum_{b \in \mathcal{B}} \sum_{c \in \mathcal{C}} e_{i,m,t,c,b}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}. \quad (17)$$

The supply flows are allocated across public charger types and the two residual demand classes through $e_{i,m,t,c,b}$. Privately supplied home charging is excluded.

PV generation bounds. PV generation can either be used directly to serve public charging demand or routed to the BESS for later use. PV export to the upstream grid is not allowed. This import-only grid interface isolates the value of PV and BESS for serving CPO charging demand. Feed-in remuneration, electricity-market participation, and export-capacity conditions are outside the model scope. The following constraint in Eq. (18) limits PV use in each interval by the available generation potential implied by installed PV capacity and the corresponding PV capacity factor.

$$p_{i,m,t}^{\text{dir}} + p_{i,m,t}^{\text{batt}} \leq K^{\text{PV}} N_i^{\text{PV}} f_{m,t}^{\text{PV}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}. \quad (18)$$

Here, $p_{i,m,t}^{\text{batt}}$ denotes PV energy routed to BESS charging, K^{PV} denotes the rated energy output per PV panel and interval, and $f_{m,t}^{\text{PV}}$ is the month and interval specific PV capacity factor. PV installation is also limited by the site specific maximum number of panels, constrained by available land use area (Section 5.3).

$$0 \leq N_i^{\text{PV}} \leq \bar{N}_i^{\text{PV}}, \quad N_i^{\text{PV}} \in \mathbb{Z}_+, \quad \forall i \in \mathcal{I}. \quad (19)$$

Therefore, the right hand side of Eq. (18) represents the maximum PV energy that can be generated and used locally in zone i during slot (m, t) . Unused PV generation is implicitly curtailed. The model does not require an explicit curtailment variable.

3.5. Grid electricity tariffs and charging revenue

This subsection defines the tariff inputs used in the objective function. These are the retail electricity price paid by the CPO for grid procurement and the charger type specific tariffs charged to users for charging.

Electricity retail pricing. Hourly day ahead wholesale electricity prices p_t^{spot} (öre/kWh) are converted into the retail grid electricity tariff $\rho_{m,t}$ (SEK/kWh) faced by the CPO in month m and half-hour interval t .

$$\rho_{m,t} = \left(\frac{p_t^{\text{spot}}}{100} + \text{TAX} + \text{GRID} + \text{MARKUP} \right) (1 + \text{VAT}), \quad (20)$$

where TAX, GRID, and MARKUP are expressed in SEK/kWh (excluding VAT), and VAT is dimensionless. The index $t' = \lceil t/\tau \rceil$ maps interval t to the corresponding hourly spot-price observation, where τ denotes the number of operational intervals per hour.

Charging revenue. Daily charging revenue in month m is computed by applying the charger type tariff ϖ_c to energy delivered by public chargers across all zones, intervals, and demand classes (Eq. (2)). This accounting excludes energy served by private home chargers but includes residual home demand that is supplied by CPO-operated public chargers.

3.6. User redirection and acceptable incentive

Spatial redirection is modeled as a short-range demand-side flexibility mechanism that reallocates a portion of public charging demand from one zone to nearby zones within a prescribed travel-distance limit. Each redirected trip receives compensation for the generalized cost of the modeled detour. In the revised formulation, redirected energy is also indexed by the charger type assigned at the origin and the charger type used at the destination. This allows the model to account for charging-tariff differences when redirected demand is served by a costlier destination charger type. The formulation therefore consists of feasible user redirection arc generation, distance-based filtering, trip-based incentive calculation, charger-type accounting, and capacity-coupling of redirected demand at the destination.

Feasible user-redirection arc generation. The optimization model takes as input a set of distance-feasible candidate redirection arcs constructed upstream from road network shortest path distances between planning zones. Pairs whose shortest-path distance does not exceed a tunable threshold $d_{\max}$ are retained as candidate redirection arcs with network distance d_{ij} . This preprocessing ensures that user redirection feasibility is based on network accessibility rather than Euclidean distance. The set $\mathcal{D}$ contains all distance-feasible candidate arcs, while the active set $\mathcal{A}$ further filters these arcs to retain only interval combinations with non-negligible baseline public demand.

$$\begin{aligned} \mathcal{D} &= \{(i, j) \in \mathcal{I} \times \mathcal{I} \mid i \neq j, d_{ij} \leq d_{\max}\}, \\ \mathcal{A} &= \{(i, j, m, t) \in \mathcal{D} \times \mathcal{M} \times \mathcal{H} \mid D_{i,t,\text{public}} + D_{j,t,\text{public}} > D_{\min}^{\text{arc}}\}. \end{aligned} \quad (21)$$

Here, $D_{i,t,\text{public}} \equiv D_{i,m,t,\text{public}}$ denotes the month-invariant representative-day public demand defined in Section 3.1. The threshold $D_{\min}^{\text{arc}}$ suppresses arc-slot pairs with negligible combined baseline public demand. This interval filter is repeated across months because the demand profile is unchanged. Outgoing-flow constraints separately prevent redirection from an origin without available public demand.

Detour compensation rule. The model applies a deterministic compensation rule rather than estimating individual acceptance probabilities. An eligible redirection for which the modeled compensation is paid is treated as behaviorally admissible under the scenario assumption. Empirical studies show that willingness to accept charging flexibility depends strongly on perceived time cost and incentives [38,45]. Here, spatial redirection is paired with an explicit incentive that compensates the generalized time disutility of a short detour to a nearby charging location, including driving and walking time. In addition, if the redirected demand is served by a destination charger type with a higher tariff than the assigned origin charger type, the positive tariff difference is compensated through $\Delta_{c^o, c^d}^{\text{price}}$.

$$T_{i,j} = c^{\text{detour}} d_{ij}, \quad c^{\text{detour}} = v_{\text{time}} \left(\frac{1}{v_{\text{car}}} + \frac{2}{v_{\text{walk}}} \right). \quad (22)$$

Here, v_{time} denotes the value of time (VoT), while v_{car} and v_{walk} denote average driving and walking speeds, respectively. The coefficient c^{detour} has units of SEK/km, so $T_{i,j} = c^{\text{detour}} d_{ij}$ represents the compensation paid for one redirected trip on arc (i, j) . The two walking terms approximate access and return walking time around the redirected charging location.

Redirected energy is linked to trips through a nominal redirected-energy quantum κ (kWh per redirected trip). This allows incentives to be modeled at the trip level while still accommodating aggregate redirected energy volumes that are not exact multiples of κ . Equivalently, defining $\gamma_{i,j} := T_{i,j}/\kappa$ yields a per kWh incentive coefficient for the residual tail component, while the full-trip component remains represented by $n_{i,j,m,t}^{\text{full}}$.

$$\begin{aligned} z_{i,j,m,t} &= \kappa n_{i,j,m,t}^{\text{full}} + u_{i,j,m,t}^{\text{tail}}, \\ n_{i,j,m,t}^{\text{full}} &\in \mathbb{Z}_+, \quad \forall (i, j, m, t) \in \mathcal{A}. \end{aligned} \quad (23)$$

The variable $z_{i,j,m,t}$ represents the total redirected energy on physical arc (i, j) in slot (m, t) , while z_{i,j,m,t,c^o,c^d} retains the charger-type pairing needed for tariff-compensation and type-consistency accounting through Eq. (5).

$$0 \leq u_{i,j,m,t}^{\text{tail}} \leq (\kappa - \varepsilon_{\text{tail}}) Y_{i,j,m,t}, \quad \forall (i, j, m, t) \in \mathcal{A}. \quad (24)$$

Here, $\varepsilon_{\text{tail}} > 0$ is a small numerical constant used to represent $u_{i,j,m,t}^{\text{tail}} < \kappa$ in closed MILP form. The variable $n_{i,j,m,t}^{\text{full}}$ counts complete κ -sized redirected trip bundles, whereas $u_{i,j,m,t}^{\text{tail}}$ represents the remaining redirected energy below one nominal trip quantum. The estimated number of redirected trips used in the results is reconstructed in post-processing as follows.

$$N_{ijmt}^{\text{redir}} = n_{i,j,m,t}^{\text{full}} + \mathbb{I}\{u_{i,j,m,t}^{\text{tail}} > 0\}.$$

Here, $\mathbb{I}\{\cdot\}$ is the indicator function, equal to one when the stated condition holds and zero otherwise. A positive residual tail is identified using the numerical tolerance applied in post-processing.

Origin and destination charger type accounting. The variable z_{i,j,m,t,c^o,c^d} denotes redirected public charging energy from origin zone i to destination zone j in slot (m, t) , where c^o is the origin charger type used for tariff-reference accounting and c^d is the destination charger type used to serve the redirected energy. To avoid treating the origin charger type as a purely nominal label, the auxiliary variable $w_{i,m,t,c}^{\text{orig}}$ is introduced to represent the portion of baseline public charging demand in zone i and slot (m, t) assigned to charger type c before redirection accounting.

$$\sum_{c \in \mathcal{C}} w_{i,m,t,c}^{\text{orig}} + e_{i,m,t,\text{public}} = D_{i,m,t,\text{public}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}. \quad (25)$$

$$\sum_{j: (i,j,m,t) \in \mathcal{A}} \sum_{c^d \in \mathcal{C}} z_{i,j,m,t,c^o,c^d} \leq w_{i,m,t,c^o}^{\text{orig}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}, c^o \in \mathcal{C}. \quad (26)$$

$$w_{i,m,t,c}^{\text{orig}} = e_{i,m,t,c,\text{public}} - \sum_{j: (j,i,m,t) \in \mathcal{A}} \sum_{c^o \in \mathcal{C}} z_{j,i,m,t,c^o,c} + \sum_{j: (i,j,m,t) \in \mathcal{A}} \sum_{c^d \in \mathcal{C}} z_{i,j,m,t,c,c^d}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}, c \in \mathcal{C}. \quad (27)$$

Eq. (27) links the origin charger-type allocation to the optimized public charging allocation. The first term on the right-hand side is the public charging energy served by charger type c in zone i . Incoming redirected energy served by charger type c is subtracted because it did not originate as baseline demand in zone i . Outgoing redirected energy assigned to origin charger type c is added because it belongs to the baseline public demand of zone i , although it is physically served at another zone. Eq. (26) ensures that outgoing user redirection assigned to a given origin charger type cannot exceed the baseline public demand allocated to that type. Outgoing user redirection from an origin zone is also bounded by the total baseline public demand available in that zone and slot, as specified in Eq. (16).

Similarly, incoming redirected energy assigned to destination charger type (c^d) must be included in the public charging energy actually served by that charger type at the destination zone.

$$\sum_{j: (j,i,m,t) \in \mathcal{A}} \sum_{c^o \in \mathcal{C}} z_{j,i,m,t,c^o,c^d} \leq e_{i,m,t,c^d,\text{public}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}, c^d \in \mathcal{C}. \quad (28)$$

Eq. (28) prevents the destination charger-type index from becoming a purely nominal label. The inequality is used because $e_{i,m,t,c^d,\text{public}}$ may include both incoming redirected demand and non-redirection local public demand served by the same charger type.

User-redirection activation and installed capacity bound. The binary variable $Y_{i,j,m,t} \in \{0, 1\}$ indicates whether user redirection arc (i, j) is activated in slot (m, t) . If an arc is activated, a minimum redirected energy volume $\kappa_{\min}$ must be satisfied, and the aggregate redirected flow $z_{i,j,m,t}$ is bounded by an installed capacity based big- M term at destination zone j . The condition $\kappa_{\min} \leq \kappa$ ensures that the minimum open-arc flow requirement remains consistent with the nominal redirected trip quantum. A valid site level upper bound can be selected as $M_j^{\text{redir}} = \bar{C}_j^{\text{pub}} \max_{c \in \mathcal{C}} \{K_c / a_c^{\text{chg}}\}$, which links the user redirection big- M value to the destination installation resource and the maximum charger capacity density.

$$\kappa_{\min} Y_{i,j,m,t} \leq z_{i,j,m,t}, \quad \forall (i, j, m, t) \in \mathcal{A}. \quad (29)$$

$$z_{i,j,m,t} \leq M_j^{\text{redir}} Y_{i,j,m,t}, \quad \forall (i, j, m, t) \in \mathcal{A}. \quad (30)$$

$$z_{i,j,m,t} \leq \sum_{c \in \mathcal{C}} K_c x_{j,c}, \quad \forall (i, j, m, t) \in \mathcal{A}. \quad (31)$$

Here, K_c denotes the per-interval service capacity of charger type c . Eq. (31) bounds aggregate redirected energy by the installed charger capacity available at the destination zone. Destination-side charger type consistency is enforced separately through Eq. (28), while demand conservation is enforced through the public demand balance in Eq. (15). Together with the charger-capacity constraint in Eq. (13), these constraints ensure that redirected public charging demand assigned to destination charger type c^d is physically served by the corresponding installed charger type at the destination zone.

3.7. BESS charging and discharging modeling and scheduling

The BESS provides temporal flexibility by storing electricity from either the grid or on-site PV generation and discharging it in later intervals. Within the model, BESS operation supports retail tariff responsive energy shifting and improved local utilization of PV generation, subject to SoC dynamics, efficiency losses, non simultaneous charging/discharging, and installation limits.

BESS energy state dynamics. For the stored-energy variable, the boundary index $\ell \in \mathcal{H}_0$ is used. The variable $\chi_{i,m,\ell}$ denotes stored BESS energy in zone i and month m at boundary ℓ . The value $\chi_{i,m,0}$ is the stored energy before the first half hour interval, while $\chi_{i,m,t}$ is the stored energy after interval $t \in \mathcal{H}$. All charging, discharging, PV, tariff, and demand variables remain indexed only over operational intervals ($t \in \mathcal{H}$).

Each installed BESS unit has an energy capacity (Cap^{batt}) in kWh/unit. The number of installed BESS units in zone i is denoted by B_i , so the installed BESS energy capacity is $\text{Cap}^{\text{batt}} B_i$. The maximum charge or discharge energy that one BESS unit can exchange within one half-hour interval is denoted by K^{batt} . Equivalently, if a BESS unit is parameterized by a storage duration H^{batt} in hours, then $K^{\text{batt}} = \text{Cap}^{\text{batt}} / (H^{\text{batt}} \tau)$ ($\tau = 2$ for half-hour intervals).

$$\chi_{i,\text{Jan},0} = \sigma^{\text{init}} B_i \text{Cap}^{\text{batt}}, \quad \forall i \in \mathcal{I}, \quad \chi_{i,m,0} = \chi_{i,m^-, \text{end}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M} \setminus \{\text{Jan}\}. \quad (32)$$

Here, m^- denotes the representative month immediately preceding m in the ordered monthly sequence.

$$\chi_{i,m,t} = \chi_{i,m,t-1} + \eta_{\text{ch}} \left(g_{i,m,t}^{\text{batt}} + p_{i,m,t}^{\text{batt}} \right) - \frac{1}{\eta_{\text{dis}}} d_{i,m,t}^{\text{dis}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}. \quad (33)$$

Here, $t_{\text{end}} = 48$ denotes the last interval of the representative day. Eq. (32) fixes the January initial stored energy at the fraction σ^{init} of installed BESS energy capacity and links the initial energy state of each subsequent monthly representative day to the terminal energy state of the preceding month. No cyclic closure is imposed between the terminal energy state of December and the initial energy state of January. Eq.

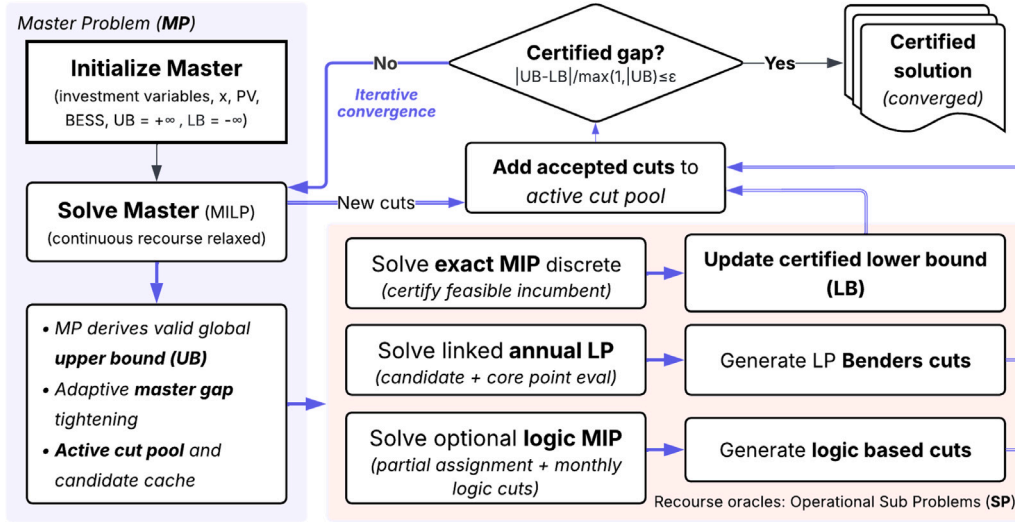


Fig. 3. Implemented LBBB workflow. Exact linked 12-month BESS recourse is preserved in the annual LP and MIP oracles.

(33) updates stored energy over each operational interval $t \in \mathcal{H}$. The parameter σ^{init} defines the initial SoC fraction, B_i is the number of installed BESS units at zone i , and Cap^{batt} is the energy capacity of one battery unit. The parameters η_{ch} and η_{dis} denote charging and discharging efficiencies, respectively. The variables $g_{i,m,t}^{\text{batt}}$ and $p_{i,m,t}^{\text{batt}}$ represent grid and PV energy routed into BESS charging, while $d_{i,m,t}^{\text{dis}}$ represents BESS discharge allocated to demand satisfaction at the public charging bus.

The SoC linkage is applied across representative monthly operating profiles to reduce artificial resets between monthly profiles. Since each month is represented by one weighted typical day rather than by a fully chronological sequence of repeated daily operations, the monthly day weights do not enter the SoC transition equations. This linkage should therefore be interpreted as a representative-period continuity approximation, not as an explicit reconstruction of everyday battery cycling or seasonal storage. The resulting BESS schedules characterize strategic planning outcomes under month-specific tariff and PV conditions rather than a fully chronological operational dispatch trajectory.

BESS energy state bounds. To preserve BESS health and operational flexibility, stored energy is restricted to the range implied by the configured minimum and maximum SoC fractions.

$$\underline{\sigma} B_i \text{Cap}^{\text{batt}} \leq \chi_{i,m,\ell} \leq \bar{\sigma} B_i \text{Cap}^{\text{batt}}, \quad \forall i \in \mathcal{I}, m \in \mathcal{M}, \ell \in \mathcal{H}_0. \quad (34)$$

BESS throughput, charging and discharging exclusivity bounds. The BESS charge and discharge throughput in each interval is limited by the number of installed BESS units. Let K^{batt} denote the maximum charge or discharge energy per BESS unit in one half-hour interval. These constraints ensure that a site with more installed BESS units has proportionally higher charge and discharge capability, which corresponds to assuming that BESS energy capacity and power-conversion capacity are deployed proportionally. Non-simultaneous charging and discharging is enforced through the binary operating-mode variable $\delta_{i,m,t}$. Let M_i^{batt} denote a valid constant site-level upper bound on total BESS charging or discharging energy in zone i per half-hour interval. For a clean MILP formulation, this big- M parameter is defined from the exogenous installation bound as $M_i^{\text{batt}} := K^{\text{batt}} \bar{B}_i$. The physical throughput is separately bounded by the installed unit count through $K^{\text{batt}} B_i$, while M_i^{batt} is used only for mode exclusivity. This prevents unrealistically fast charging or discharging, ensures zero BESS flow when no battery unit is installed, and avoids products between the binary mode variable

and the integer BESS installation variable.

$$\begin{aligned} g_{i,m,t}^{\text{batt}} + p_{i,m,t}^{\text{batt}} &\leq K^{\text{batt}} B_i, \\ d_{i,m,t}^{\text{dis}} &\leq K^{\text{batt}} B_i, \\ \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}. \end{aligned} \quad (35)$$

$$\begin{aligned} g_{i,m,t}^{\text{batt}} + p_{i,m,t}^{\text{batt}} &\leq M_i^{\text{batt}} \delta_{i,m,t}, \\ d_{i,m,t}^{\text{dis}} &\leq M_i^{\text{batt}} (1 - \delta_{i,m,t}), \\ \forall i \in \mathcal{I}, m \in \mathcal{M}, t \in \mathcal{H}. \end{aligned} \quad (36)$$

Here, $K^{\text{batt}} B_i$ represents the physical installed throughput limit, while $M_i^{\text{batt}} = K^{\text{batt}} \bar{B}_i$ is a constant site-level big- M bound used only to enforce the binary operating mode.

BESS installation bounds. The number of battery units that can be installed in spatial zone i is restricted by a site-specific upper bound.

$$0 \leq B_i \leq \bar{B}_i, \quad B_i \in \mathbb{Z}_+, \quad (37)$$

where $\bar{B}_i$ reflects the maximum battery units deployment permitted at site i by spatial or regulatory constraints. This resulting annual MILP is solved using the LBBB method presented in Section 4.

4. Solution methodology

The monolithic formulation discussed in the earlier Section 3 jointly determines long-term charging infrastructure investments and detailed annual operation. At city scale, the coupling of infrastructure decisions with user redirection, discrete trip and activation logic, and linked PV and BESS operation makes the resulting MILP computationally demanding. The implemented LBBB method exploits the natural separation between long-term infrastructure planning and the annual operational problem induced by a fixed infrastructure configuration [46–48]. LBBB is used here as an established decomposition method rather than claimed as a new generic algorithm. The solution-method contribution is thus application-specific. The master retains strategic charger, PV, and BESS decisions together with a continuous annual operational relaxation, while fixed-infrastructure mixed-integer evaluations restore the discrete user-redirection relationships omitted from that relaxation and provide certified feasible incumbents.

Fig. 3 summarizes the implemented procedure. The master problem selects infrastructure and maintains an embedded continuous operational relaxation, while fixed candidates are evaluated through linked annual LP, exact annual MIP, and optional logic-based subproblems. Valid cuts refine the master, and convergence is assessed from the global master upper bound and the best certified feasible lower bound.

4.1. Master problem with operational relaxation

The master retains the infrastructure decisions and embeds continuous user redirection and PV and BESS relaxations that preserve the principal operational couplings. Its annual profit approximation is progressively refined by the cuts summarized in Section 4.3, with their detailed construction provided in Appendix A.

Let $\xi = (\{x_{i,c}\}_{i \in I, c \in C}, \{N_i^{PV}\}_{i \in I}, \{B_i\}_{i \in I}) \in \mathcal{X}$, denote an infrastructure configuration, where $\mathcal{X}$ is defined by the charger, PV, and BESS installation constraints in Eqs. (12), (19), and (37). For fixed infrastructure ξ , the exact operating value and planning problem are defined here.

$$Q(\xi) = \max_{y \in \mathcal{Y}(\xi)} \Pi^{\text{op}}(y; \xi), \quad (38)$$

$$\max_{\xi \in \mathcal{X}} \{-C^{\text{inv}}(\xi) + Q(\xi)\}. \quad (39)$$

Here, y collects the exact annual operational variables introduced in the monolithic formulation. The LBB master provides an upper approximation of Eq. (39) while retaining a continuous representation of the principal service, user redirection, and energy system relationships.

The master is therefore a strengthened MILP relaxation rather than an investment only model. It retains the integer investment variables $x_{i,c}$, N_i^{PV} , and B_i , together with their strategic feasibility constraints. Bounded investment variables are also linked to auxiliary binary encodings used to formulate reusable and threshold based logic cuts. These auxiliary variables do not constitute additional infrastructure decisions. For each representative month m , interval t , and connected user redirection component $q \in Q_{m,t}$, the master includes the component slot value variable $\theta_{m,t,q}$. These variables represent disaggregated upper approximations of the corresponding grid baseline operating profit contributions. The scalar variable η represents total annual CPO profit after accounting for PV and BESS energy effects and annualized infrastructure cost.

Master problem objective. The iteration- k LBB master maximizes the total annual profit approximation.

$$\text{MP}_k : \max_{\xi, \hat{y}, \eta, \theta} \eta. \quad (40)$$

The relationship between the total profit variable and the disaggregated component slot values is stated in Eq. (41).

$$\eta \leq \sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{H}} \sum_{q \in Q_{m,t}} \theta_{m,t,q} + E^{\text{cred}} - C^{\text{inv}}(\xi). \quad (41)$$

Thus, $\theta_{m,t,q}$ plays the role of a disaggregated operational value approximation, whereas η is the master objective and collects all annual operating and investment terms. This distinction also allows annual LP and exact configuration cuts to restrict total profit directly without altering the component level relaxation. The component cap is defined from total component demand and the largest nonnegative grid baseline charging margin.

$$\bar{\theta}_{mq} = N_m^{\text{days}} \max \left\{ 0, \max_{c \in C} (\varpi_c - \rho_{m,t}) \right\} D_{mq}, \quad (42)$$

where D_{mq} is the total home and public demand associated with component q in slot (m, t) . Together with Eq. (41), the master constraints are summarized here.

$$\begin{aligned} \text{s.t. } \quad & \xi \in \mathcal{X}, \quad \hat{y} \in \hat{\mathcal{Y}}(\xi), \\ & \eta \leq \bar{\eta}, \\ & \theta_{m,t,q} \leq \bar{\theta}_{mq}, \quad q \in Q_{m,t}, \\ & \eta \leq a^\ell + (\beta^\ell)^\top \xi, \quad \ell \in \mathcal{K}_k^\eta, \\ & \theta_{m,t,q} \leq h_{mq}^r(\xi), \\ & r \in \mathcal{K}_{m,t,q,k}^\theta, \quad q \in Q_{m,t}. \end{aligned} \quad (43)$$

Here, $\hat{y}$ collects the continuous service, user redirection, slack, PV-BESS, and SoC variables retained in $\hat{\mathcal{Y}}(\xi)$. The sets $\mathcal{K}_k^\eta$ and $\mathcal{K}_{m,t,q,k}^\theta$ index

the accumulated annual-profit and component level cuts, respectively. The quantity $\bar{\eta}$ is a valid upper bound on annual profit, while E^{cred} represents the grid-cost correction associated with the relaxed PV and BESS operation. The affine functions $a^\ell + (\beta^\ell)^\top \xi$ and $h_{mq}^r(\xi)$ denote the corresponding annual and component level upper bound cuts.

Continuous service and user redirection relaxation. The master represents residual home service, local public service, aggregate public demand redirection, charger-type service, and unmet demand using continuous variables. Let $\hat{e}_{imt}^{\text{home}}$ denote residual home energy served locally, $\hat{e}_{imt}^{\text{loc}}$ public demand served at its origin, $\hat{z}_{i,j,m,t}$ aggregate redirected public energy, and $\hat{e}_{imtc}$ total energy served by charger type c .

$$\hat{e}_{imt}^{\text{home}} + \hat{e}_{i,m,t,\text{home}} = D_{i,m,t,\text{home}}. \quad (44a)$$

$$\hat{e}_{imt}^{\text{loc}} + \sum_{j:(i,j,m,t) \in \mathcal{A}} \hat{z}_{i,j,m,t} + \hat{e}_{i,m,t,\text{public}} = D_{i,m,t,\text{public}}. \quad (44b)$$

$$\sum_{c \in C} \hat{e}_{imtc} = \hat{e}_{imt}^{\text{home}} + \hat{e}_{imt}^{\text{loc}} + \sum_{j:(j,i,m,t) \in \mathcal{A}} \hat{z}_{j,i,m,t}. \quad (44c)$$

$$\hat{e}_{imtc} \leq K_c x_{i,c}. \quad (44d)$$

$$\hat{z}_{i,j,m,t} \geq 0. \quad (44e)$$

Eqs. (44a)–(44d) apply for all applicable $i \in I$, $m \in \mathcal{M}$, $t \in \mathcal{H}$, and $c \in C$, while Eq. (44e) applies for all $(i, j, m, t) \in \mathcal{A}$.

Residual home demand remains local, whereas public demand may be served at its origin or redirected through an eligible arc. Incoming redirected energy is incorporated into destination service, which remains bounded by the installed charger-type capacity. These relationships provide a continuous relaxation of the home and public demand balances in Eqs. (14) and (15), together with the charger capacity constraint in Eq. (13). For component q , the initial grid baseline operating profit estimate is bounded by Eq. (45).

$$\begin{aligned} \theta_{m,t,q} \leq N_m^{\text{days}} \left[\sum_{i \in I_{m,t,q}} \sum_{c \in C} (\varpi_c - \rho_{m,t}) \hat{e}_{imtc} \right. \\ \left. - c^{\text{slack}} \sum_{i \in I_{m,t,q}} \sum_{b \in \mathcal{B}} \hat{e}_{i,m,t,b} \right. \\ \left. - \sum_{(i,j) \in \mathcal{A}_{m,t,q}} \gamma_{i,j} \hat{z}_{i,j,m,t} \right]. \end{aligned} \quad (45)$$

Eq. (45) initially treats served energy as grid supplied and applies the charger-type tariff, unmet demand penalty, and continuous per kWh user redirection incentive used in the monolithic objective. Since $\gamma_{i,j} = T_{i,j}/\kappa$, the distance term is consistent with the combined full-trip and residual tail incentive in Eq. (6). The relaxation does not retain the full origin type-destination type user redirection tensor, tariff compensation cost, binary arc activation, minimum active arc flow, integer trip bundles, or residual tail logic. These discrete relationships are reinstated when the exact annual MIP subproblem is evaluated.

Linked PV and BESS relaxation. The master additionally contains a linked annual energy relaxation. Let $\hat{p}_{imt}^{\text{dir}}$ and $\hat{p}_{imt}^{\text{batt}}$ denote direct PV use and PV-to-BESS charging, $\hat{g}_{imt}^{\text{batt}}$ grid-to-BESS charging, $\hat{d}_{imt}^{\text{dis}}$ BESS discharge, and $\hat{x}_{im\ell}$ stored BESS energy at boundary ℓ . The grid baseline profit in Eq. (45) is corrected through Eq. (46).

$$E^{\text{cred}} = \sum_{i \in I} \sum_{m \in \mathcal{M}} \sum_{t \in \mathcal{H}} N_m^{\text{days}} \rho_{m,t} \left(\hat{p}_{imt}^{\text{dir}} + \hat{d}_{imt}^{\text{dis}} - \hat{g}_{imt}^{\text{batt}} \right). \quad (46)$$

Direct PV use and BESS discharge reduce grid procurement, whereas grid-to-BESS charging introduces an additional grid cost. Direct grid supply is implicit as the remaining service not supplied by direct PV or BESS discharge. The master preserves the principal PV and BESS relationships.

$$\hat{p}_{imt}^{\text{dir}} + \hat{p}_{imt}^{\text{batt}} \leq K^{\text{PV}} N_i^{\text{PV}} f_{m,t}^{\text{PV}}. \quad (47a)$$

$$\hat{p}_{imt}^{\text{dir}} + \hat{d}_{imt}^{\text{dis}} \leq \sum_{c \in C} \hat{e}_{imtc}^{\text{dis}}. \quad (47b)$$

$$\hat{g}_{imt}^{\text{batt}} + \hat{p}_{imt}^{\text{batt}} \leq K^{\text{batt}} B_i. \quad (47c)$$

$$\hat{d}_{imt}^{\text{dis}} \leq K^{\text{batt}} B_i. \quad (47d)$$

$$\hat{\chi}_{imt} = \hat{\chi}_{im,t-1} + \eta_{\text{ch}} (\hat{g}_{imt}^{\text{batt}} + \hat{p}_{imt}^{\text{batt}}) - \hat{d}_{imt}^{\text{dis}} / \eta_{\text{dis}}. \quad (47e)$$

Eqs. (47a)–(47e) apply for all $i \in \mathcal{I}$, $m \in \mathcal{M}$, and $t \in \mathcal{H}$. The stored energy bounds in Eq. (34) are retained, together with the annual boundary conditions.

$$\begin{aligned} \hat{\chi}_{i,\text{Jan},0} &= \sigma^{\text{init}} \text{Cap}^{\text{batt}} B_i, \\ \hat{\chi}_{im0} &= \hat{\chi}_{i,m^-, \text{end}}, \quad m \in \mathcal{M} \setminus \{\text{Jan}\}. \end{aligned} \quad (48)$$

Thus, the configured January initial SoC and month-to-month representative period continuity are preserved. The master relaxes the binary charge–discharge mode restriction in Eq. (36). This operating mode exclusivity is restored in the exact annual MIP subproblem.

4.2. Operational subproblems

At iteration k , the LBB master produces an infrastructure candidate $\bar{\xi}^{(k)}$. Each operational subproblem fixes this candidate and evaluates the resulting annual or component level operation without redesigning the infrastructure. These evaluations provide feasible objective values, candidate-specific bounds, or valid inequalities for strengthening the master. The term oracle is used only generically to denote such a fixed infrastructure evaluation.

4.2.1. Linked annual LP subproblem

The linked annual LP subproblem is obtained from the complete monolithic formulation by imposing the infrastructure fixing equalities.

$$\begin{aligned} x_{i,c} &= \bar{x}_{ic}^k, \quad i \in \mathcal{I}, c \in C, \\ N_i^{\text{PV}} &= \bar{N}_i^{\text{PV},k}, \quad i \in \mathcal{I}, \\ B_i &= \bar{B}_i^k, \quad i \in \mathcal{I}, \end{aligned} \quad (49)$$

where $\bar{\xi}^{(k)} = (\{\bar{x}_{ic}^k\}, \{\bar{N}_i^{\text{PV},k}\}, \{\bar{B}_i^k\})$. All binary and general integer variable domains are then relaxed. The complete annual objective in Eq. (1), the twelve representative months, and the linked BESS chronology in Eqs. (32) and (33) remain unchanged. For cut generation directly in the total-profit variable η , let

$$\Pi(\mathbf{y}; \xi) = -C^{\text{inv}}(\xi) + \Pi^{\text{op}}(\mathbf{y}; \xi),$$

denote the complete annual objective. Because ξ is fixed in the operational subproblem, its investment cost is constant.

$$\Phi^{\text{LP}}(\bar{\xi}^{(k)}) = \max_{\mathbf{y} \in \mathcal{Y}^{\text{LP}}(\bar{\xi}^{(k)})} \Pi(\mathbf{y}; \bar{\xi}^{(k)}), \quad (50)$$

where $\mathcal{Y}^{\text{LP}}(\bar{\xi}^{(k)})$ denotes the continuous relaxation of the annual operational feasible set obtained by relaxing all binary and general-integer domains, and Π is the complete annual profit objective, including the fixed annualized investment cost.

Let $\lambda_{ic}^{x,k}$, $\lambda_i^{\text{PV},k}$, and $\lambda_i^{B,k}$ denote the dual multipliers associated with the charger, PV, and BESS fixing equalities in Eq. (49), respectively. The equalities are written in the same variable equals fixed-value orientation used in the implementation. LP duality gives the affine upper bound cut as defined here.

$$\eta \leq \alpha^k + \sum_{i \in \mathcal{I}} \sum_{c \in C} \lambda_{ic}^{x,k} x_{i,c} + \sum_{i \in \mathcal{I}} \lambda_i^{\text{PV},k} N_i^{\text{PV}} + \sum_{i \in \mathcal{I}} \lambda_i^{B,k} B_i. \quad (51)$$

where the intercept is,

$$\begin{aligned} \alpha^k &= \Phi^{\text{LP}}(\bar{\xi}^{(k)}) - \sum_{i \in \mathcal{I}} \sum_{c \in C} \lambda_{ic}^{x,k} \bar{x}_{ic}^k \\ &\quad - \sum_{i \in \mathcal{I}} \lambda_i^{\text{PV},k} \bar{N}_i^{\text{PV},k} - \sum_{i \in \mathcal{I}} \lambda_i^{B,k} \bar{B}_i^k. \end{aligned} \quad (52)$$

No sign restriction is imposed on the dual coefficients. Because the LP relaxes the exact fixed infrastructure operational model, $\Phi^{\text{LP}}(\bar{\xi}^{(k)})$ upper bounds the corresponding exact annual profit. Eq. (51) is consequently a valid global upper bound cut for the profit maximization master. The linked annual LP is evaluated at both the current infrastructure candidate and a running core point. The latter provides an additional valid LP cut but does not involve an auxiliary Pareto cut selection problem. The running core-point update and cut-acceptance procedure are detailed in Appendix A.1.

4.2.2. Exact annual MIP subproblem

The exact annual MIP subproblem reuses the complete monolithic formulation with the infrastructure vector fixed at $\bar{\xi}^{(k)}$.

$$\Phi^{\text{MIP}}(\bar{\xi}^{(k)}) = \max_{\mathbf{y} \in \mathcal{Y}(\bar{\xi}^{(k)})} \Pi(\mathbf{y}; \bar{\xi}^{(k)}). \quad (53)$$

The term *exact* refers to the operational formulation, where no discrete or operational relationship is relaxed. The model jointly optimizes all continuous, integer, and binary operational decisions under the fixed infrastructure candidate. In particular, it restores the charger type pair redirection tensor and its aggregate consistency in Eq. (5), the origin type allocation and consistency constraints, the binary arc-activation conditions in Eqs. (29)–(31), the integer trip-bundle and residual tail relationships in Eqs. (23)–(24), exact charger type service, tariff compensation, grid and PV flows, BESS mode exclusivity, linked SoC chronology, and complete slack accounting. Its objective is the same annual-profit objective as Eq. (1).

Let $\bar{\mathbf{y}}^k$ denote any feasible incumbent returned by the fixed infrastructure MIP. Its complete objective value is defined as follows.

$$Z^k = \Pi(\bar{\mathbf{y}}^k; \bar{\xi}^{(k)}), \quad \bar{\mathbf{y}}^k \in \mathcal{Y}(\bar{\xi}^{(k)}). \quad (54)$$

The pair $(\bar{\xi}^{(k)}, \bar{\mathbf{y}}^k)$ is feasible for the original monolithic MILP. Hence, Z^k provides a certified feasible lower bound for the global profit maximization problem, irrespective of whether the fixed infrastructure MIP has been solved to zero solver gap.

The solver best bound obtained from the fixed infrastructure MIP is denoted by $\bar{Z}^k$. It provides an upper bound only for the evaluated infrastructure configuration and is not used as the global LBB upper bound. Instead, it supports a configuration-dependent logic cut expressed through the auxiliary binary encodings of the bounded investment variables. The corresponding mismatch function and cut formulation are provided in Appendix A.2.

4.3. Cuts, bounds, and termination

The master is progressively strengthened by valid upper-bounding inequalities obtained from the operational subproblems. The core procedure uses the linked annual LP cut in Eq. (51), an additional LP cut evaluated at a running core point, configuration-dependent cuts derived from the exact annual MIP, and dynamic Hall/min-cut component bounds. Optional component level LP and monthly logic-MIP cuts may also be activated. Configuration-dependent and component level cuts are detailed in Appendix A.2, while cut filtering and active pool management are described in Appendix A.1.

For the profit-maximization problem, the solver best bound of the master provides global upper-bound information, whereas a feasible exact annual MIP solution provides a certified lower bound. Let $\text{BestBd}(\text{MP}_k)$ denote the solver best bound from the iteration- k master. The running bounds are updated as follows.

$$\widetilde{\text{UB}}^{(k)} = \min \{ \text{UB}^{(k-1)}, \text{BestBd}(\text{MP}_k) \}. \quad (55a)$$

$$\text{LB}^{(k)} = \max \{ \text{LB}^{(k-1)}, Z^k \}. \quad (55b)$$

$$\text{UB}^{(k)} = \max \{ \text{LB}^{(k)}, \widetilde{\text{UB}}^{(k)} \}. \quad (55c)$$

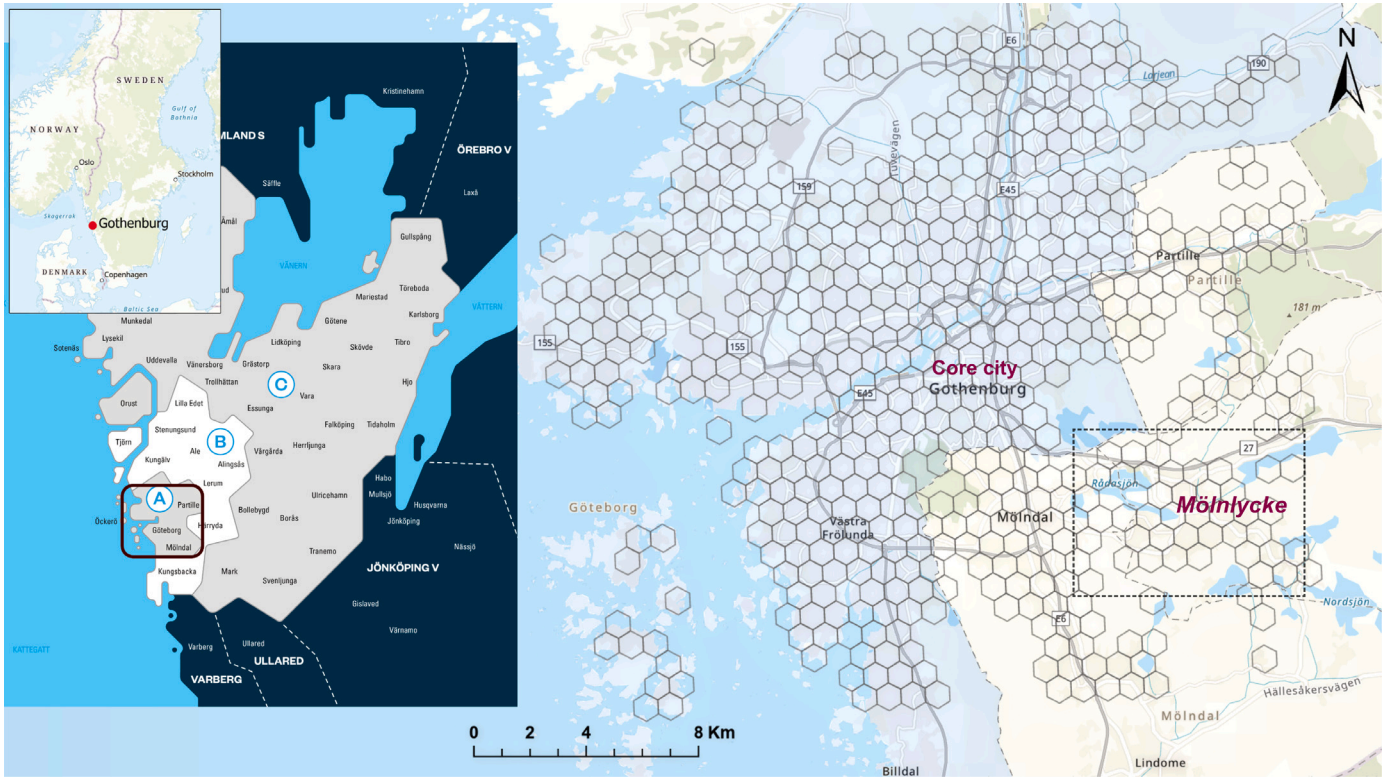


Fig. 4. Västtrafik Zone A in the Gothenburg metropolitan area, comprising Göteborg, Mölndal, Partille, and Öckerö.

Eq. (55b) is applied whenever the exact annual MIP returns a feasible value Z^k . Otherwise, the preceding lower bound is retained. The final maximum in Eq. (55c) prevents a minor numerical inversion of the reported bounds. Neither the master incumbent objective nor the candidate-specific MIP bound $\bar{Z}^k$ is substituted for the global upper bound.

The certified relative gap is defined as follows.

$$\text{Gap}^{(k)} = \frac{\max \{0, \text{UB}^{(k)} - \text{LB}^{(k)}\}}{\max \{1, |\text{UB}^{(k)}|\}}. \quad (56)$$

The algorithm terminates with a certified LBBD solution when,

$$\text{Gap}^{(k)} \leq \epsilon_{\text{LBBD}}. \quad (57)$$

Adaptive master-gap tightening, candidate caching, repeated-evaluation avoidance, and explicit stagnation handling control the computational effort of the iterative procedure without modifying the feasible region or the bound definitions above. Their implemented rules are described in Appendix A.3.

The decomposition avoids embedding the complete exact, charger type aware annual operational block in every master solve, while the exact fixed infrastructure MIP preserves feasible solution certification. The following sections present the resulting city scale planning outcomes and assess the convergence and computational performance of the decomposition.

5. Case study

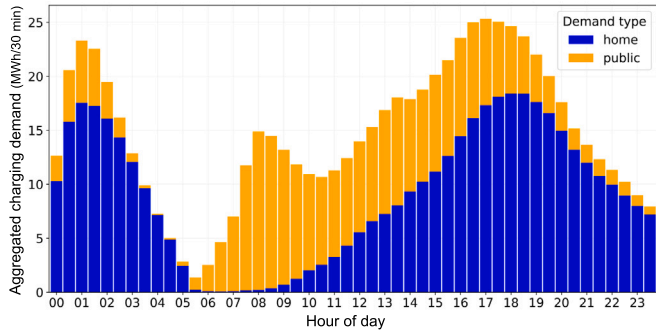
The optimization framework is applied to Västtrafik Zone A in the Gothenburg metropolitan area, Sweden. Zone A comprises the municipalities of Göteborg, Mölndal, Partille, and Öckerö.¹ The spatial

domain is represented by 638 hexagonal planning zones. Fig. 4 shows the study area, while the following subsections describe the charging demand, temporal, siting, and economic inputs used by the optimization. Across four municipalities, the 638-zone representation retains substantial spatial variation in charging demand, land-use inputs, and road-network connectivity. It therefore provides a heterogeneous city-region application for testing the integrated formulation, while the numerical outcomes remain specific to the Gothenburg case.

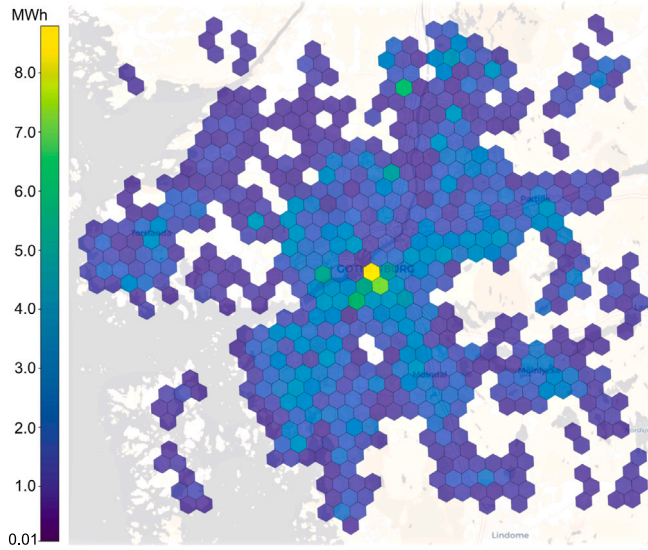
5.1. Spatiotemporal charging demand data

Charging events are obtained from the activity-based MATSim framework described in [13] and aggregated to the spatial and temporal resolution of the optimization ($|I| = 638$, $|M| = 12$, and $|H| = 48$). The synthetic population contains approximately 557 220 agents. Up to 106 000 agents are represented as EV users, corresponding to a 50% EV penetration assumption among the eligible car using population. The charging demand generation simulation, including the 10% population sample and its scaling considerations for synthetic-population-equivalent charging demand aggregation, is established in relevant studies [13]. The optimization uses the resulting aggregated charging events as exogenous inputs. Charging events are generated from activity chains and charging decisions that account for charger accessibility, charging prices, dwell duration, and ToU aware rescheduling. Events are classified as home, work, or public charging. Work and public events are combined into the public demand class, whereas home events are first assigned to exogenous private home charging capacity. Only the resulting residual home demand enters the CPO optimization. The aggregated values $D_{i,m,t,b}$ provide the optimization demand input. A representative daily demand profile is repeated across the twelve representative months. Monthly variation is introduced through month-specific day weights, electricity prices, and PV availability. The optimization does not rerun agent-based demand simulations, modify EV adoption, or endogenously update individual charging behavior.

¹ Västtrafik, “ABC-zoner”, <https://www.vasttrafik.se/reseplanering/abc/>, accessed May 7, 2025.



(a) Daily charging demand by interval and demand class.



(b) Spatial distribution of daily charging demand.

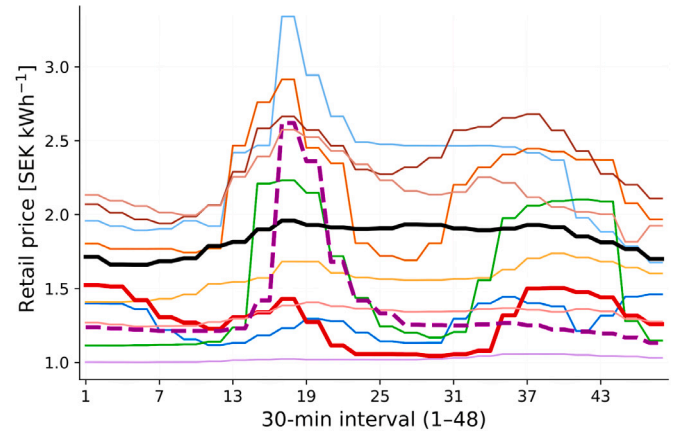
Fig. 5. Spatiotemporal charging demand inputs used by the optimization.

Fig. 5(a) shows the representative daily demand profile, while Fig. 5(b) illustrates its spatial heterogeneity across the planning zones. These profiles define $D_{i,m,t,b}$ in the demand balance and capacity constraints and determine the public demand volumes eligible for short-range user redirection (Sections 3.3 and 3.6).

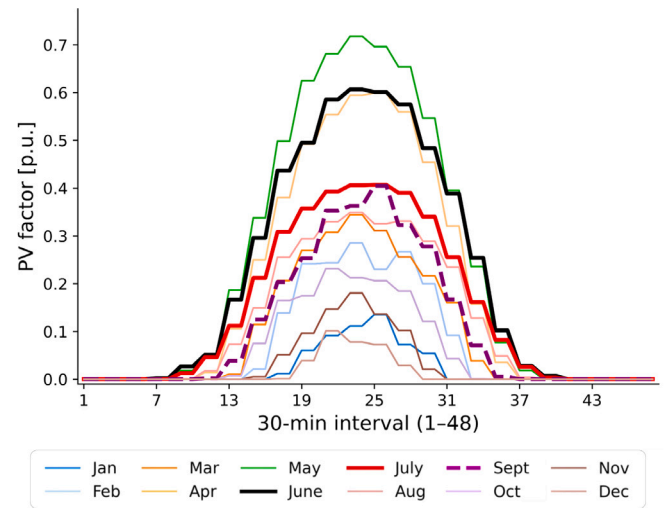
5.2. Temporal variability in electricity tariffs and PV inputs

The optimization uses month-varying inputs to represent seasonality through retail ToU electricity tariffs ($\rho_{m,t}$) and PV capacity factors ($f_{m,t}^{PV}$). Fig. 6 summarizes their representative profiles used for Gothenburg.

Retail electricity tariffs. Representative hourly day-ahead electricity price profiles were derived from Nord Pool Market Data API² and mapped to the two half-hour intervals within each hour. The wholesale component is converted to the retail procurement price $\rho_{m,t}$ through Eq. (20). The tariff construction adds fixed model assumptions of 0.375 SEK/kWh for the electricity-tax component, 0.45 SEK/kWh for the distribution network component, and 0.02 SEK/kWh for the retailer margin, followed by 25% VAT. These values constitute a common tariff calibration for the scenario analysis and should not be interpreted as



(a) Retail (ToU) electricity tariffs.



(b) PV capacity factors.

Fig. 6. Representative monthly retail electricity tariff and PV capacity-factor profiles used in the Gothenburg case study.

a customer specific electricity contract or as the statutory Swedish tax rate for 2025.

The input tariffs are higher in winter and vary within the day. Winter months (December–February) average approximately 2.00 SEK/kWh, compared with 1.50 SEK/kWh in summer (June–August; Fig. 6(a)). Peak-to-off-peak spreads exceed 0.50 SEK/kWh and reach 0.70 SEK/kWh on spring mornings. These profiles enter the grid procurement cost in Eq. (3).

Solar PV capacity factors. The interval-specific PV capacity factors $f_{m,t}^{PV}$ are derived from hourly PV output data obtained from the JRC Photovoltaic Geographical Information System (PVGIS) [49] for Gothenburg. The hourly series is aggregated into representative monthly daily profiles and normalized by the nominal PV system capacity.

The annual (2023) data extraction uses PVGIS 5.3, a fixed-plane inclination of 35 degrees, azimuth 0 degrees, and a system loss assumption of 14%. These settings,³ influence the resulting capacity factors. The profiles represent regional planning inputs rather than

² Nord Pool Market Data API v2 (OpenAPI) <https://data-api.nordpoolgroup.com/index.html>, accessed February 11, 2025.

³ PVGIS user manual: https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis/using-pvgis-5/pvgis-5-user-manual_en, accessed May 7, 2025.

Table 2
Infrastructure specifications and tariff parameters used in the case study.

Infrastructure asset	Unit specification	CapEx (SEK/unit)	Life (yr)	Tariff (SEK/kWh) ^d
Pedestal <i>slow</i> charger ^a	11 kW AC	25 000	10	5.50
Pedestal <i>medium</i> charger ^a	22 kW AC	40 000	10	6.00
Pedestal DC <i>fast</i> charger ^a	50 kW DC	350 000	10	6.50
Fixed on-site solar PV panel ^b	0.5 kW _p	5 000	25	–
Battery energy storage unit ^c	10 kWh/5 kW	34 000	15	–

Notes: Public charging tariffs are fixed scenario values. The PV panel CapEx assumes a 500 W_p fixed on-site module and a representative Swedish turnkey cost of 10 SEK/W. The BESS unit assumes 10 kWh energy capacity, 5 kW power capacity, and 2 h energy to power ratio.

^a Charger CapEx values represent turnkey Swedish public or semi-public deployment assumptions, informed by Swedish AC/DC charger and installation-cost guidance from [Parkit](#) and [Länsstyrelsen](#).

^b PV CapEx is based on Swedish turnkey PV prices from [IEA-VPVS Sweden 2024](#). The siting bounds follow the parking-canopy and candidate public-surface method described in Section 5.3.

^c BESS CapEx uses a central Swedish installation cost estimate of 3400 SEK/kWh from the [Wingren and Johnsson \(2018\)](#) thesis on BESS for fast active disturbance reserve. ([Svenska kraftnät, 2018](#)).

^d Public charging tariffs are calibrated against Gothenburg municipal AC charging and Swedish CPO price levels, using [Parkering Göteborg](#), [Mer Sweden](#), and [Circle K Sweden](#).

site-validated production forecasts. Zone-specific shading, roof orientation, snow accumulation, inverter sizing, and local structural conditions are not modeled. PV generation is limited by Eq. (18). The factors show a strong summer–winter contrast at Gothenburg’s latitude (57.7°N), as shown in Fig. 6. These aggregated profiles support zone-level planning [50].

5.3. Land use and infrastructure constraints

Public charger and PV installation bounds enter the optimization through Eqs. (12) and (19), respectively. Assumed private home charger availability is applied during preprocessing to construct the residual input $D_{i,m,t,home}$.

Public parking capacity. The site resource limit $\bar{C}_i^{pub}$ is derived from the estimated number of public parking spaces within zone i . Parking records are compiled from Göteborgs Stad’s ParkingService API,⁴ municipal open data registers for the Zone A municipalities, and OpenStreetMap features tagged separately as `amenity=parking` or `amenity=charging_station`.

Spatially deduplicated parking records are aggregated by zone to define an installation resource budget. Charger type c consumes a_c^{chg} resource units in Eq. (12). These calibrated bounds support strategic siting rather than specifying one charger per recorded space, consistent with parking-based approaches in [51,52].

Parking-area PV potential. PV installation limits are estimated from mapped parking footprints, candidate public land, and 2024–2025 Copernicus Sentinel-2 multispectral imagery. Because the Sentinel-2 multispectral bands have spatial resolutions of 10, 20, or 60 m, with 10 m resolution available for the visible and near-infrared bands used for detailed land surface screening, the imagery is used for area classification rather than parcel-level delineation. Mapped parking polygons are treated as technically eligible for canopy PV, while 10% of other classified suitable public surfaces is assumed to be practically usable. These are planning assumptions used to translate candidate surface area into upper bounds on installed panel-equivalent capacity. They do not account for ownership, shading, structural loading, canopy foundations, grid connection, or permitting. The resulting panel counts define $\bar{N}_i^{PV}$ in Eq. (19).

Residential home charger availability. Private home chargers are treated as exogenous assets outside the CPO investment boundary. Although national and aggregate residential charging statistics are available, no complete geocoded inventory of private home chargers covering all Zone A municipalities was available for this study [53,54]. Private

charging is therefore represented through a scenario based partial access assumption. This preprocessing assumption distinguishes demand represented as privately supplied from residual home demand entering CPO planning. It is not interpreted as an estimate of actual private charger ownership in each cell.

Eligible residential buildings are identified from OpenStreetMap tags with a minimum footprint of 25 m². Early Swedish EV adopters have predominantly occupied detached houses, while apartment residents rely more on public charging [55]. The prepared baseline assigns one 7 kW home charger to 50% of eligible buildings, after which the implemented preprocessing adds five assumed chargers per cell as a calibration margin. The 50% share and the five-charger addition are scenario inputs, not observed regional penetration rates. Each assumed charger supplies up to 3.5 kWh per half-hour interval during preprocessing, and only the remaining home demand enters $D_{i,m,t,home}$. For context, official 2024 municipal statistics report that small houses comprise approximately 17.6% of Göteborg’s housing stock and rental tenure 53.5% of dwellings.⁵ These municipal figures do not describe every cell or municipality in the wider Västrafik Zone A study area and are not used to infer socioeconomic equity. Demographic and income equity are not modeled.

Road network and user redirection eligible arcs. Road network distances are calculated from OpenStreetMap extracts containing links accessible to private vehicles. Each hexagonal zone centroid is connected to the nearest eligible road network node within 500 m, and shortest path distances d_{ij} are calculated using Dijkstra’s algorithm. Candidate redirection arcs satisfy $d_{ij} \leq d_{max}$ and define D (Section 3.6). In the baseline case, $d_{max} = 1.5$ km. The active month–slot set additionally retains only tuples satisfying a strict demand screening condition as follows, which sets the arcs eligible for user-redirection.

$$D_{i,t,public} + D_{j,t,public} > D_{min}^{arc}$$

The sensitivity analysis (Section 6.7) evaluates sensitivity to distance thresholds of 1.2 and 2.0 km.

5.4. Infrastructure costs and charging tariffs

Table 2 lists representative investment and tariff inputs rather than procurement quotations [56]. Monetary values are expressed in Swedish kronor (SEK); grid procurement uses the VAT-inclusive tariff in Eq. (20). Infrastructure costs are annualized at $r = 6\%$ using Eq. (8), with $N_{days}^{yr} = 365$ in Eq. (1).

⁴ Göteborgs Stad, *ParkingService* v2.3 API, <https://data.goteborg.se/ParkingService/v2.3/help>, accessed May 7, 2025.

⁵ Göteborgs Stad, Stadsledningskontoret, *Göteborgsbladet 2025—områdesfakta*, <https://goteborg.se/wps/portal/enheter/statistik-och-analys/statistik/faktablad/goteborgsbladet>.

Table 3

Summary of annual infrastructure, energy, and economic outcomes across technology and user redirection scenarios.

	Sc01: Chargers only		Sc02: Chargers + PV		Sc03: Chargers+PV+BESS	
	No redir.	With redir.	No redir.	With redir.	No redir.	With redir.
Charging infrastructure						
Slow chargers (11 kW)	508	207	508	205	508	206
Medium chargers (22 kW)	2 335	2 245	2 335	2 180	2 335	2 179
Fast chargers (50 kW)	168	172	168	176	168	176
Public charger capacity (kWh/30 min)	32 679	30 134	32 679	29 508	32 679	29 502
PV panels (500 W)	–	–	65 473	69 382	78 944	80 762
Battery units (10 kWh)	–	–	–	–	2 473	2 342
Energy flows (kWh/yr)						
Grid electricity purchased	115 273 211	115 273 211	92 165 211	89 250 365	83 832 541	82 501 060
Direct grid supply to chargers	115 273 211	115 273 211	92 165 211	89 250 365	79 326 787	78 311 450
Grid energy to BESS	–	–	–	–	4 505 754	4 189 610
PV electricity used locally	–	–	23 108 000	26 022 846	32 614 638	33 902 120
Direct PV supply to chargers	–	–	23 108 000	26 022 846	25 402 863	26 807 433
PV energy to BESS	–	–	–	–	7 211 775	7 094 687
Battery discharge	–	–	–	–	10 543 561	10 154 329
Redirected public charging demand	–	957 375	–	2 972 347	–	2 082 558
Est. user-redirected charging trips/yr	–	170 935	–	557 616	–	366 560
Share of public demand redirected	–	0.97%	–	3.00%	–	2.10%
PV use relative to charging demand	–	–	20.05%	22.57%	28.29%	29.41%
Annual economic terms (SEK/yr)						
Public charging revenue	707 210 725	708 241 157	707 210 725	709 039 788	707 210 811	708 737 416
Grid electricity cost	200 160 082	200 160 082	161 571 170	156 350 014	143 250 857	141 136 180
User-redirectation incentive cost	–	1 266 613	–	4 717 847	–	3 152 047
Distance compensation	–	1 266 613	–	4 717 847	–	3 152 047
Price compensation	–	0	–	0	–	0
Unmet demand penalty	0	0	0	0	0	0
Annualized charger CapEx	22 404 586	21 083 274	22 404 586	20 913 440	22 404 586	20 911 402
Annualized PV and BESS CapEx	–	–	25 608 716	27 137 659	39 535 041	39 787 524
Net profit	484 646 058	485 731 189	497 626 253	499 920 828	502 020 327	503 750 264
Net profit gain vs Sc01 no-redir.	–	1 085 131	12 980 196	15 274 771	17 374 269	19 104 206
Net profit gain from user redirection	–	1 085 131	–	2 294 575	–	1 729 937

Public charger costs use Swedish turnkey planning estimates [57]. The PV assumption of 10 SEK/W excludes site-specific canopy and civil works, while the cited BESS cost is a calibration value rather than a current quotation. Charger ratings are converted to interval capacities through $K_c = \text{Power}_c / \tau$. Public charging tariffs and PV/BESS costs remain fixed across scenarios; redirection parameters are varied separately.

Road geometry, parking and land-use records, spot prices, and PVGIS profiles are externally derived inputs. Private charging access, usable PV area, tariffs, asset costs and lifetimes, and detour compensation are scenario assumptions. Section 6.7 tests the behavioral and spatial redirection parameters.

6. Numerical analysis and results

This section reports the optimal infrastructure, spatial user redirections, energy demand-supply, economic, PV–BESS operations, and sensitivity outcomes of the Gothenburg case study across scenarios. All energy and cost metrics are annualized by scaling representative day outcomes in month m by N_m^{days} and correspond to the converged solution of the proposed optimization framework.

6.1. Scenario analysis

Table 3 compares three technology configurations: chargers only, chargers with PV, and chargers with PV and BESS. Each technology configuration is evaluated with and without spatial user redirection under the same spatiotemporal inputs (Section 5), allowing the marginal effects of redirection on infrastructure, energy flows, and annual economics to be compared directly.

Scenario 01: chargers only. All charging energy is purchased from the grid. Redirection leaves total grid purchases unchanged because all demand remains served, but reduces installed charging capacity by 7.8% and annualized charger cost by 5.9%. The reduction is concentrated in slow chargers, while higher-power capacity is retained selectively. Incentive payments partly offset these savings, yielding a 0.22% profit increase. Without PV or BESS, redirection therefore acts mainly through spatial consolidation of charging capacity.

Scenario 02: chargers with PV. Without redirection, PV leaves charger deployment unchanged and reduces grid purchases by 20.0%. Its main effect is on energy sourcing because demand locations remain fixed. Enabling redirection reduces charger count by 14.9%, increases local PV use by 12.6%, and further reduces grid purchases by 3.2%. This configuration has the largest redirected volume and a 0.46% profit gain from redirection.

Scenario 03: chargers with PV and BESS. Without redirection, adding BESS to the PV case reduces grid purchases by 9.0%, increases local PV use by 41.1%, and raises profit by 0.88%. Within the combined configuration, redirection reduces charger count by 14.9%, charging capacity by 9.7%, and grid purchases by 1.6%. PV deployment increases by 2.3% and BESS units decrease by 5.3%. The 29.9% lower redirected volume than in the PV-only case suggests partial substitution between spatial flexibility and storage.

All six cases serve the modeled demand without penalty. Charger deployment is identical across the no-redirection cases, while redirection allows investment and energy decisions to adjust jointly. All reported redirection payments compensate distance. Tariff compensation is zero. The following subsections examine Scenario 03 with redirection.

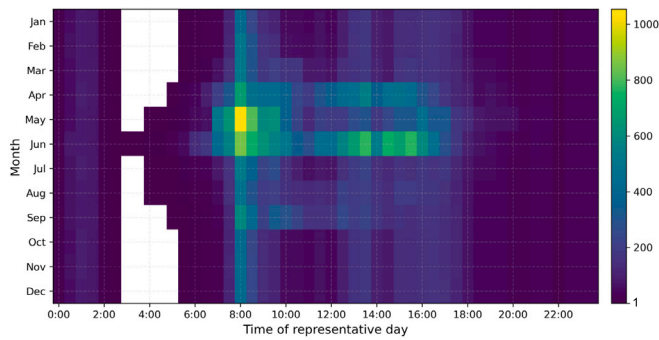


Fig. 7. Annualized redirected public-charging energy by representative month and half-hour interval, aggregated across study-region arcs.

6.2. Spatial user redirection

Scenario 03 redirects 2.08 GWh/year, equivalent to 2.10% of annual public-destination demand and 366 560 reconstructed trips. Redirection is limited in volume but varies across space and time. Its energy-weighted mean distance is 1.05 km within the 1.5-km eligibility limit, with compensation averaging approximately SEK 1.51 per redirected kWh. Tariff compensation is zero relative to the model's assigned origin tariff references. Local PV use rises by 3.9% compared with the corresponding no-redirection case, equivalent to approximately 0.62 additional kWh per redirected kWh. This ratio reflects jointly optimized investments and operation, rather than an isolated effect of redirection. Approximately 75.0% of redirected energy has a fast-charger tariff reference and 25.0% a medium reference. At the destination, 51.8% is served by medium chargers and 48.1% by fast chargers. Slow-charger service is negligible. These reference categories are model allocations, not observed individual charging requirements.

Fig. 10 illustrates selected April corridors where positive redirection connects demand zones to nearby zones with installed PV, BESS, and public charging capacity. Infrastructure is fixed annually, whereas the displayed arrows represent operation during a selected month. Fig. 7 shows how redirected energy varies by month and time of day. April–June account for approximately 46.4% of annual redirected energy, with June contributing 19.2%, May 14.2%, and April 13.0%. The largest representative-day month-slot flow occurs in May around 08:00 and reaches approximately 1.05 MWh. June exhibits both a pronounced morning band and a second period of elevated redirection during the afternoon.

The spring and early-summer concentration coincides with higher PV availability, but also reflects tariffs, charging capacity, BESS operation, network distances, and compensation costs. The seasonal pattern cannot be attributed to PV availability alone.

6.3. Demand–supply balance

Fig. 8 presents the annual weighted average representative day demand and supply balance for the combined PV, BESS, and redirection case. The positive bars distinguish residential charging demand from work and public demand, while negative bars show private home charging and CPO supply from the grid, direct PV, and BESS discharge.

Private home charging supplies much of the residential demand during overnight and evening periods. Residual home demand and public-destination demand are supplied through the optimized public charging network. The latter is distributed more broadly over the early evening periods, producing a system profile with different temporal requirements for private and public infrastructure. For the CPO-served demand, direct grid supply accounts for 67.9% of annual charging energy, direct PV supply accounts for 23.3%, and BESS discharge supplies the remaining 8.8%. Consequently, the network remains grid

dependent, but PV and BESS replace almost one-third of the energy that would otherwise need to be supplied directly from the grid. Direct PV supply is concentrated in daylight intervals and offsets grid imports when PV availability overlaps with charging demand. Of the 33.90 GWh/year of locally used PV electricity, 26.81 GWh is supplied directly to chargers and 7.09 GWh is routed to BESS charging. The BESS extends the use of this locally generated electricity beyond the solar-production window and also charges from the grid during selected lower cost intervals. The supply decomposition in Fig. 8 represents the energy source delivered to each demand class. Grid and PV energy used to charge BESS therefore appears later as BESS discharge rather than as direct supply. Spatial redirection does not change total system demand. It reallocates part of public demand toward zones with available capacity and lower-cost energy.

6.4. Public charger infrastructure

Fig. 9 shows the spatial deployment of public chargers in Scenario 03 with redirection. Marker size represents the number of chargers of each type installed within a planning zone, while the green network indicates eligible short-range redirection connections. The optimized network contains 2 561 public chargers distributed across 529 of the 638 planning zones. Medium chargers account for 85.1% of installed public chargers and 81.2% of the available half-hourly public charging capacity. They are installed in 511 zones, making the 22 kW technology the main coverage layer. This reflects its lower investment cost per unit of capacity relative to fast charging and its suitability for sustained urban demand.

Fast chargers constitute 6.9% of installed units and 14.9% of public charging capacity. Their higher unit cost favors selective deployment. They account for approximately 40.0% of annualized charger investment cost despite representing less than 7% of charger count. The map (Fig. 9) shows fast chargers dispersed along major transport corridors and at selected urban and peripheral demand nodes. Most zones contain about two fast chargers. This pattern is consistent with fast charging being used as targeted high-throughput or peak-serving capacity rather than as the primary network technology. Lower-demand peripheral zones generally receive medium chargers or no public infrastructure where nearby capacity and redirection accessibility are sufficient. Slow chargers account for 8.0% of installed units but only 3.8% of available capacity and 1.1% of supplied energy. They are installed in 93 zones and are substantially more spatially concentrated than the other charger types. The ten largest slow-charger zones contain approximately 52% of all slow chargers. Several such clusters coincide with central activity and transport locations having large public-parking resource bounds. The siting data commonly represents larger parking facilities as on-ground, underground, or multilevel parking.

Public capacity responds to the demand remaining after private home charging has been accounted for and excluded. Zones with greater residual residential demand, intensive public activity, or limited substitution through nearby sites require more public capacity. Conversely, the availability of redirection, PV, and BESS allows some demand to be served at better supplied neighboring zones. The resulting deployment therefore reflects the interaction of spatiotemporally varying demand, parking-based siting limits, road-network accessibility, and local energy resources rather than a uniform charger-to-population ratio.

6.5. PV and BESS infrastructure

Fig. 10 shows the installed PV and BESS capacities for Scenario 03 with redirection, together with representative user-redirection flows in April. The infrastructure decisions are annual and fixed, whereas the arrows illustrate month-specific redirections. The solution installs 80 762 panel equivalents, corresponding to 40.38 MW of nominal PV capacity, and 2 342 BESS units, corresponding to 23.42 MWh of energy

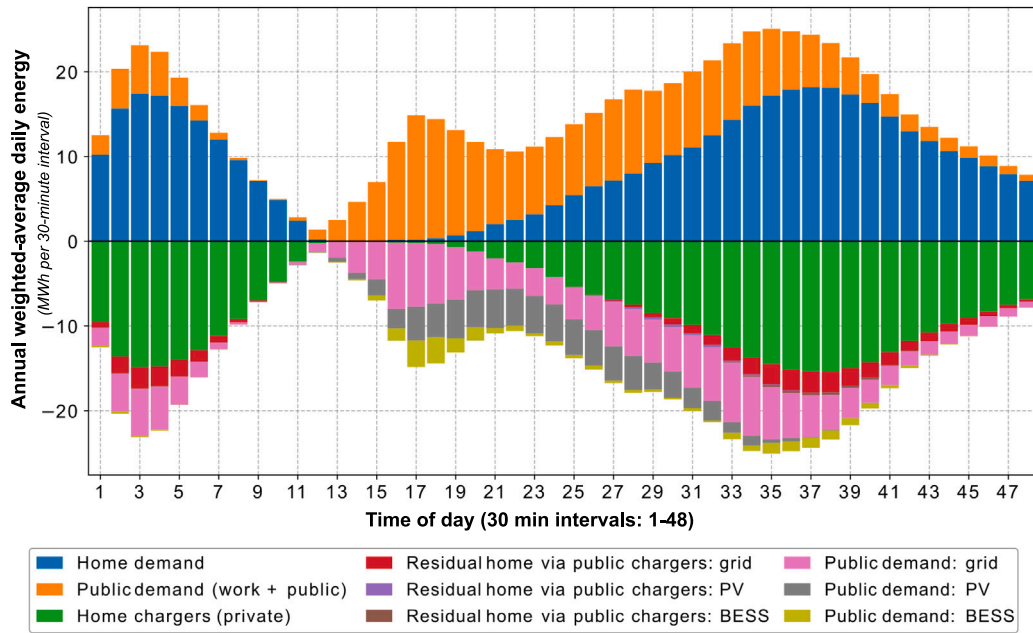


Fig. 8. Annual-weighted representative-day charging demand (positive vertical axis) and energy-supply composition (negative vertical axis), aggregated across the study region.

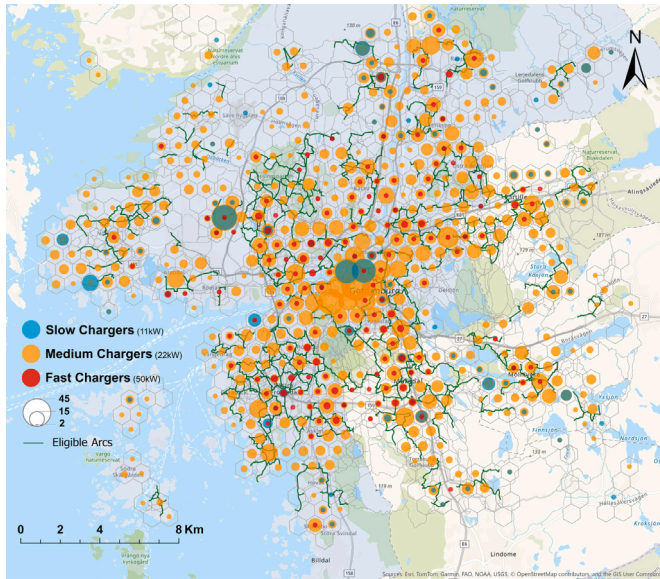


Fig. 9. Optimized public charger counts by type and planning cell for Scenario 03 with user redirection.

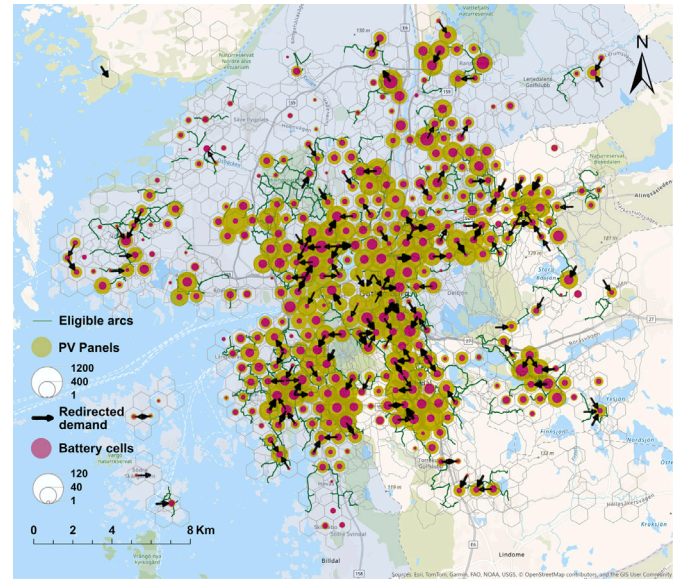


Fig. 10. Optimized annual PV-panel and BESS-unit deployment with positive Scenario 03 user-redirection flows in April.

capacity and 11.71 MW of charge/discharge power. PV panels are installed in 383 zones and BESS units in 375 zones. Every BESS-hosting zone also contains PV and public charging capacity, while only eight PV hosting zones do not contain BESS. This near complete co-location indicates that storage is selected primarily where it can shift locally generated electricity for subsequent charging use temporally.

The spatial deployment follows the principal urban demand and transport corridors while remaining constrained by the zone-specific PV and public parking bounds. Larger PV and BESS installations occur where charging demand, available installation area, and opportunities to serve nearby redirected demand coincide. Since PV export is excluded, installed PV has economic value only when its output can be used directly, stored, or used to support additional charging demand

redirected into the zone. Of the 33.90 GWh/year of locally used PV electricity, 79.1% is supplied directly to chargers and 20.9% is routed to BESS charging. Total annual BESS charging is 11.28 GWh, of which 62.9% is supplied by PV and 37.1% by the grid. Annual discharge is 10.15 GWh, corresponding to an aggregate output-to-input energy ratio of approximately 90.0%. The 1.13 GWh input–output difference reflects conversion losses and the representative-period energy-state boundaries.

Fig. 11 illustrates the spatially averaged BESS operation for the April representative day. Grid charging occurs mainly in low-cost early intervals of the day, while PV charging dominates during daylight hours. Discharge occurs during demand periods outside the main PV production window. Positive charging and negative discharging can

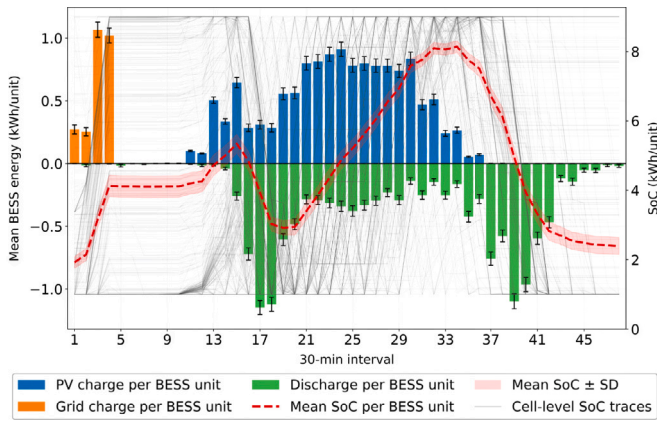


Fig. 11. Spatially averaged battery charging and discharging on the April representative day.

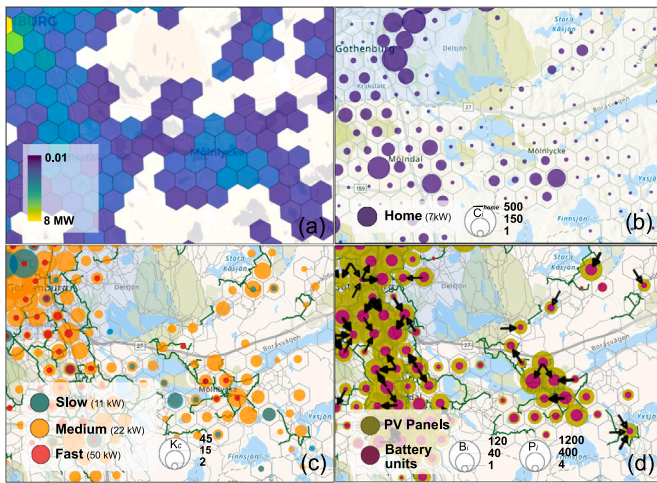


Fig. 12. Local interactions at the southeastern boundary of the study area toward Mölnlycke: (a) spatial charging demand, (b) assumed exogenous private home chargers, (c) optimized public charger counts, and (d) installed PV panels and BESS units with representative positive redirection flows in June.

appear in the same aggregate interval because different zones may operate differently, although the zone-level mode constraint prevents simultaneous charging and discharging within an individual BESS.

Relative to the PV-only redirection case, the combined configuration reduces grid purchases by 7.5%, lowers grid costs by 9.7%, and raises profit by 0.77%. BESS extends local PV use beyond its production window, while the lower redirected volume indicates partial substitution between temporal and spatial flexibility.

6.6. Local insights

Fig. 12 illustrates demand, exogenous private home charging, optimized public chargers, and PV/BESS investments with April redirection flows near Mölnlycke. Panel (b) is a preprocessing input; panels (c) and (d) show optimized infrastructure.

Lakes, green areas, and sparse road connections interrupt eligible redirection routes, so Euclidean proximity does not ensure accessibility. Positive June flows follow connected corridors toward zones with charging capacity and local energy resources. The example illustrates how network connectivity and siting limits shape the use of compensated spatial flexibility.

6.7. Sensitivity of user redirection assumptions

A sensitivity analysis is conducted for the assumptions entering the generalized user redirection incentive cost and feasible redirection set. The tested parameters are the assumed EV travel speed v_{car} , value of time v_{time} , and maximum redirection distance d_{max} . Each parameter is varied around the baseline to identify the local model response around a specified reference configuration [58]. Table 4 reports the resulting annual profit, redirected energy, estimated redirected trips, and local PV use.

$$\text{Local response/sensitivity ratio} = \frac{\Delta y (\%) }{\Delta x (\%)},$$

where x is the tested parameter (ΔChange) and y is the outcome (ΔProfit , $\Delta\text{Redir.}$, or $\Delta\text{PV use}$). These ratios are individual local responses and should not be interpreted as global sensitivity indices.

EV travel speed. Changing v_{car} affects the driving-time component of the detour incentive. Reducing speed from 30 to 10 km/h (−66.67%) decreases the redirected energy by 33.33%, while increasing speed to 40 km/h (+33.33%) raises it by 6.76%. The corresponding redirected energy response ratios are 0.50 and 0.20, respectively, indicating that redirected energy changes less than proportionally to travel speed variation. The intermediate 20 km/h (−33.33%) case gives a similar but weaker response ratio of 0.29. Local PV use follows the same direction, but with much smaller ratios, as 0.021, 0.015, and 0.012 across the tested speed cases. Annual profit is least sensitive, with response ratios below 0.002. This suggests that travel speed and thus lower detour costs affect the operational intensity of redirection, allowing additional demand to reach zones with available charging capacity or local energy resources.

Value of time. The value of time produces the largest response. Reducing v_{time} from 80 to 50 SEK/h (−37.50%), increases redirected energy by 154.11% and annual profit by 0.40%. While increasing v_{time} to 100 SEK/h (25.00%), decreases redirected energy by 42.03%, and annual profit 0.13%. The corresponding response ratios are −4.11 and −1.68, showing a strong inverse relationship between the value of time and redirection intensity. Estimated redirected trips follow the same pattern, with response ratios of −2.73 and −1.37. Local PV use also responds in the expected direction, increasing by 4.46% in the low- v_{time} case (−37.50%) and decreasing by 1.71% in the high- v_{time} case (+25.00%), corresponding to PV-use response ratios of −0.119 and −0.068. Annual profit is less sensitive, changing by +0.40% and −0.13%, respectively. This pattern follows directly from the incentive formulation in Eq. (22). A lower VoT reduces the compensation required for a given detour and expands the set of profitable origin–destination assignments. The VoT assumption is therefore the dominant behavioral parameter for the realized amount of spatial redirection. But its impact on total profit remains bounded because the additional operational savings are partly offset by the infrastructure, energy, and incentive trade-offs already internalized by the model.

Maximum redirection distance. The maximum redirection distance determines which neighboring zones can be considered as feasible alternatives. Reducing d_{max} from 1.5 to 1.2 km (−20.00%) decreases redirected energy by 28.02%, while increasing it to 2.0 km (+33.33%) raises redirected energy by 29.47%. The corresponding response ratios are 1.40 and 0.88, respectively. Thus, redirected energy responds more than proportionally when the feasible radius is tightened, but less than proportionally when it is expanded beyond the baseline. Local PV use decreases by 1.06% in the 1.2 km case (−20.00%) and increases by 2.92% in the 2.0 km case (+33.33%), giving response ratios of 0.053 and 0.088. Annual profit changes by only −0.10% in the −20.00% case and +0.19% in the +33.33% case. The baseline 1.5-km threshold therefore captures many profitable short-range substitution opportunities, while additional 1.5–2.0-km connections provide further operational flexibility with modest additional profit.

Table 4

Sensitivity to behavioral and spatial redirection parameters relative to Scenario 3 baseline solution.

Parameter	Test value	Δ Change (%)	Profit (MSEK/yr)	Δ Profit (%)	Redirected (GWh/yr)	Δ Redir. (%)	Redir. trips (–)	PV use (GWh/yr)	Δ PV use (%)
Scenario 03	Baseline	–	503.75	–	2.07	–	366 560	33.87	–
<i>Baseline values: $v_{car} = 30$ km/h, $v_{walk} = 6$ km/h, $v_{time} = 80$ SEK/h, and $d_{max} = 1.5$ km.</i>									
Travel speed (EV car)	10 km/h	–66.67	503.28	–0.09	1.38	–33.33	267 280	33.39	–1.42
	20 km/h	–33.33	503.61	–0.03	1.87	–9.66	341 992	33.70	–0.50
	40 km/h	+33.33	503.81	+0.01	2.21	+6.76	387 012	34.01	+0.41
Value of time (VoT)	50 SEK/h	–37.50	505.74	+0.40	5.26	+154.11	741 685	35.38	+4.46
	100 SEK/h	+25.00	503.12	–0.13	1.20	–42.03	241 142	33.29	–1.71
Distance threshold (Max Dist)	1.2 km	–20.00	503.26	–0.10	1.49	–28.02	263 138	33.51	–1.06
	2.0 km	+33.33	504.71	+0.19	2.68	+29.47	414 837	34.86	+2.92

Overall, the sensitivity results identify the value of time v_{time} as the dominant tested parameter for redirection intensity, followed by the distance threshold (d_{max}), and then travel speed (v_{car}). Based on average absolute response ratios, VoT (v_{time}) is approximately 2.5 times more influential than distance threshold (d_{max}) and 8.8 times more influential than travel speed (v_{car}) for redirected demand. For estimated redirected trips, the corresponding ratios are approximately 2.3 and 7.9 times, respectively. For local PV use, the same ranking holds, but the contrast is smaller. As v_{time} is approximately 1.3 times more influential than d_{max} and 5.8 times more influential than v_{car} . This suggests that user redirection is likely to be more prevalent and economically beneficial in populations or regions characterized by lower time sensitivity. The distance threshold controls the spatial reach over which users can be redirected to alternative infrastructure, and thereby determines the extent to which local energy resources can be utilized. Travel speed exerts a consistent but comparatively weak influence, operating primarily through the driving-time component of the detour cost. It should be noted that these results represent local scenario sensitivities around the baseline parameter values rather than a global decomposition of model uncertainty [59], and should be interpreted accordingly. Based on average absolute response ratios, VoT is approximately 2.5 times as influential as the distance threshold and 8.8 times as influential as travel speed for redirected energy. The corresponding ratios are 2.3 and 7.9 for trip counts, and 1.3 and 5.8 for PV use. These comparisons describe the tested local perturbations, not a global uncertainty ranking or evidence of participation in other populations [59].

6.8. Computational efficiency and scalability

The full instance contains (638) planning cells, (576) month-slot blocks, and (472,800) active redirection arc-slots. Its computational burden arises from coupling strategic charger, PV, and BESS investments with temporally resolved energy operation and type-specific discrete user-redirection decisions. The LBB partition reduces the mixed-integer structure that is repeatedly optimized. The master retains the strategic investments, aggregate user redirection, and a continuous annual operational relaxation, while exact charger type-pair redirection, trip-bundle, and activation relationships are deferred to fixed-infrastructure operational evaluations. Linked annual LP evaluations strengthen the master approximation, whereas complete fixed-infrastructure MIP evaluations restore the deferred discrete relationships and provide certified feasible incumbents. For this maximization problem, the master solver best bound provides global upper-bound information and the best feasible incumbent provides the global lower bound. This distinction is important because the solver bound obtained for an individual fixed-infrastructure evaluation applies only to that infrastructure configuration and is not the global LBB upper bound.

Appendix B reports the full-scale matrix dimensions and observed resource use and compares the direct monolithic MILP, a separately implemented arc-witness Benders workflow, and LBB on a reduced benchmark. At full scale, LBB repeatedly solves a substantially smaller strategic matrix and uses approximately (19%) less observed peak

process-tree memory than the monolithic workflow. The reported monolithic solve nevertheless requires less time than the complete LBB workflow, whose sequential master, relaxation, and certification evaluations add computational effort. On the reduced benchmark, the three workflows produce near-equivalent objective values and identical aggregate charger counts, supporting formulation and implementation consistency rather than empirical field validation. Appendix C separately examines numerical-tolerance sensitivity. Denser redirection neighborhoods, finer temporal resolution, and additional charger types enlarge the operational models, particularly the type-pair redirection structure. The reported evidence therefore establishes structural reduction, lower observed peak memory, and practical solution of the tested city-scale instance.

7. Conclusion

This study integrates compensated spatial user redirection with long-term charging-point-operator (CPO) planning and operation of public chargers, on-site photovoltaic generation (PV), and battery energy storage systems (BESS). Eligible user redirection is represented as operational recourse alongside infrastructure investment and local energy operation. The formulation is evaluated for Greater Gothenburg under a scenario with 50% electric vehicle penetration. The key findings are as follows.

- Relative to the chargers-only case without redirection, the combined PV, BESS, and user-redirection case increases annual net profit by SEK 19.10 million (3.94%). Grid purchases decrease from 115.27 to 82.50 GWh/year (28.4%), while annual grid procurement cost decreases by SEK 59.02 million (29.5%). Installed public charging capacity decreases by 9.7%. All six reported scenarios return zero unmet-demand slack under the adopted penalty.
- Within the PV and BESS configuration, user redirection increases annual profit by SEK 1.73 million (0.34%), while reducing public charger count by 14.9%, installed charging capacity by 9.7%, and grid purchases by 1.6%. It reallocates 2.08 GWh/year, corresponding to 2.10% of annual public-destination demand and approximately 366 560 redirected charging trips under the adopted bundle-and-tail reconstruction. All reported redirection payments compensate distance; tariff compensation is zero. The direct profit effect is modest, but the infrastructure effect is material.
- The combined case uses 33.90 GWh/year of PV electricity locally, comprising 26.81 GWh supplied directly to chargers and 7.09 GWh routed to BESS charging. Direct grid supply, direct PV supply, and BESS discharge provide 67.9%, 23.3%, and 8.8%, respectively, of annual charging energy served by the CPO network. PV and BESS therefore account for most of the reduction in grid purchases, although grid electricity remains the principal energy source.
- The optimized combined case contains 2561 public chargers. Medium chargers account for 85.1% of installed units and provide the principal spatial coverage, whereas fast chargers are deployed selectively at higher-throughput locations.

- The application-specific logic-based Benders decomposition (LBBD) implementation separates strategic investment from complete annual operational evaluation, reducing the size of the repeatedly solved master while retaining fixed-infrastructure mixed-integer certification. The results support structural reduction and practical solution of the tested city-scale instance rather than universal runtime superiority.

The formulation represents commercial CPO investment planning rather than municipal social welfare, equity, or universal coverage. Its application to another city requires locally calibrated charging demand, road networks, private-charging access, siting limits, tariffs, solar profiles, asset costs, and redirection parameters. The reported numerical outcomes remain specific to the Gothenburg region in Sweden. Zero unmet-demand slack confirms service of the modeled demand under the adopted penalty but does not establish equal neighborhood access or distributional equity.

Certain limitations should be noted for future research. Monthly representative days do not capture day-to-day variation in charging demand or PV availability, and the linked storage profiles provide a planning-level representation rather than a fully chronological annual BESS schedule. Private charging access is scenario-based rather than derived from a complete geocoded inventory. The deterministic compensation rule does not estimate heterogeneous individual willingness to redirect, and planning zones do not identify final installation parcels. Feeder, transformer, voltage, power-flow, hosting-capacity, and grid-reinforcement constraints are excluded. Site-specific electrical feasibility must therefore be assessed before installation. Future work can examine locally recalibrated cross-city applications, access and equity criteria, empirical acceptance, stochastic or fully chronological operation, electrical-network constraints, and more efficient fixed-infrastructure certification. On the behavioral side, endogenous user acceptance models for redirection and smart charging could better represent heterogeneous preferences, incentive sensitivity, and acceptance thresholds.

CRedit authorship contribution statement

Omkar Parishwad: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Arsalan Najafi:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Ying Yang:** Writing – review & editing, Validation, Supervision, Methodology. **Kun Gao:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI-assisted technologies

During the preparation of this work, the authors used Microsoft Copilot and ChatGPT to improve the readability, language, and fluency of selected parts of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The research is supported by the Area of Advance (AoA) Transport at Chalmers University of Technology and supported by the National Natural Science Foundation of China (Grant No. 72401174). Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the sponsors' views.

Appendix A. LBBD strengthening and convergence controls

Section 4 defines the master and operational subproblems, the global bound updates, and the certified stopping criterion. This appendix presents the additional cuts and implementation controls used to strengthen the decomposition.

A.1. Running-core-point evaluation and cut-pool management

In addition to evaluation at the current infrastructure candidate, the implementation maintains a running reference point. Following its initialization at the first evaluated candidate, it is updated as follows.

$$\xi^{o,(k)} = \omega \xi^{o,(k-1)} + (1 - \omega) \bar{\xi}^{(k)}, \quad 0 < \omega < 1, \quad (58)$$

where ω is the weight assigned to the preceding running core point. The linked annual LP is independently solved at $\xi^{o,(k)}$, which may contain fractional infrastructure values after integrality relaxation. Its dual multipliers generate a second cut of the form in Eq. (51). Candidate-point and core-point cuts are added only when they violate the current master solution beyond the prescribed numerical tolerance.

Core points provide the theoretical background for several Benders cut-strengthening procedures [60,61]. The implemented routine does not, however, solve an auxiliary dual-selection problem over the optimal dual face. It is therefore described as a running-core-point-evaluated LP cut and is not claimed to be a Magnanti–Wong or Pareto-optimal cut. All candidate cuts are subjected to numerical acceptance tests before being inserted into the master. A cut is retained only when its violation exceeds the prescribed absolute or scale-adjusted relative tolerance. Solving an operational subproblem therefore does not automatically create a new master constraint. Equivalent Hall, annual-LP, component-LP, partial-logic, and configuration-cut signatures are detected and discarded. When an optional component module produces several violated inequalities, the candidates are ranked by scaled violation, and only a profile-controlled number of the strongest cuts is retained. These procedures are consistent with established Benders cut-selection and acceleration practices [60,62,63].

All accepted inequalities remain available in subsequent master solves. The active cut pool is consequently the accumulated set of nonduplicate valid annual and component level cuts. The implementation does not apply cut aging or deletion. Running-core-point evaluation is used only to obtain an additional valid annual LP cut and does not impose a stabilization region on the master variables.

A.2. Configuration-dependent and component level logic cuts

This subsection presents the configuration-dependent cut obtained from the exact annual MIP, the Hall/min-cut component bound, and the optional component level LP and MIP cuts. These inequalities strengthen the master without replacing the linked annual LP or exact annual MIP evaluations.

Exact-configuration cut. Let $\mathbf{u}$ denote the binary encoding of the bounded charger, PV, and BESS investment variables, and let $\bar{\mathbf{u}}^k$ denote the configuration evaluated by the exact annual MIP. Their mismatch is defined as follows.

$$\Delta^k(\mathbf{u}) = \sum_{r: \bar{u}_r^k = 1} (1 - u_r) + \sum_{r: \bar{u}_r^k = 0} u_r. \quad (59)$$

It satisfies $\Delta^k(\mathbf{u}) = 0$ only at the evaluated infrastructure configuration. Let $\bar{Z}^k$ be the solver best bound from the corresponding fixed infrastructure annual MIP. The configuration-dependent cut is defined as follows.

$$\eta \leq \bar{Z}^k + \left(\bar{\eta} - \bar{Z}^k \right) \Delta^k(\mathbf{u}). \quad (60)$$

At the evaluated configuration, Eq. (60) imposes the fixed-MIP upper bound. For any other configuration, $\Delta^k(\mathbf{u}) \geq 1$, and the global cap $\eta \leq \bar{\eta}$ makes the cut nonbinding.

Hall/min-cut component bound. A max-flow/min-cut separation identifies component-slot demand that cannot reach the installed charging capacity. Residual home demand can be served only in its origin zone, whereas public demand can use its origin or an eligible redirection destination. The receiving capacity of zone j is $\sum_{c \in C} K_c x_{j,c}$.

For an origin set U , let $d(U)$ denote its demand in slot (m, t) and let $\mathcal{N}(U)$ denote its reachable destination zones. A capacity deficiency occurs when $d(U)$ exceeds the installed capacity in $\mathcal{N}(U)$ [64]. Because unmet demand is allowed through penalized slack, the certificate generates a slack-preserving component-profit bound rather than a hard feasibility cut. Let D_{mtq} denote the total demand in component q .

$$\bar{\mu}_{mtq} = \max_{c \in C} \{ \varpi_c - \rho_{m,t} \}, \quad (61)$$

For a minimum-cut origin set U , the resulting slack-preserving component bound is defined here.

$$\Theta_{m,t,q} \leq N_m^{\text{days}} \left[\bar{\mu}_{mtq} D_{mtq} - (\bar{\mu}_{mtq} + c^{\text{slack}}) d(U) + (\bar{\mu}_{mtq} + c^{\text{slack}}) \sum_{j \in \mathcal{N}(U)} \sum_{c \in C} K_c x_{j,c} \right]. \quad (62)$$

The certified capacity deficiency is valued using the same unmet demand penalty as in the monolithic objective.

Component-level LP and MIP cuts. When enabled, the component LP fixes charger counts and relaxes the discrete redirection decisions. Its dual multipliers yield cuts of the form,

$$\Theta_{m,t,q} \leq a_{mtq}^r + \sum_{i \in I_{m,t,q}} \sum_{c \in C} b_{imtcq}^r x_{i,c}. \quad (63)$$

A corresponding monthly MIP restores charger type-aware redirection, arc activation, integer trip bundles, and residual tail logic.

Let $\bar{Q}_{mtq}^r$ be a valid solver upper bound obtained at charger vector $\bar{x}^r$. Since this component operating value excludes investment cost and is non-decreasing in installed charger capacity, the bound remains valid for every local charger vector satisfying $x \leq \bar{x}^r$. For each local investment variable, let v_{ic}^r be a threshold indicator satisfying,

$$v_{ic}^r = 1 \iff x_{i,c} \geq \bar{x}_{ic}^r + 1.$$

The resulting down set logic cut is defined as follows.

$$\Theta_{m,t,q} \leq \bar{Q}_{mtq}^r + (\bar{\Theta}_{mtq} - \bar{Q}_{mtq}^r) \sum_{i \in I_{m,t,q}} \sum_{c \in C} v_{ic}^r, \quad (64)$$

where $\bar{\Theta}_{mtq}$ is a valid upper bound on the component slot value. The cut applies $\bar{Q}_{mtq}^r$ over the associated down set and becomes nonbinding when at least one local charger count exceeds its evaluated threshold.

A.3. Adaptive master accuracy and repeated-candidate handling

The certified global bounds and stopping criterion are defined in Eqs. (55)–(57). The controls described below affect the accuracy and frequency of the master and subproblem evaluations but do not alter those bound definitions.

Adaptive master accuracy. Let ϵ_k^{MP} denote the requested relative MIP gap for the iteration- k master solve. Early master problems may be solved with a comparatively loose tolerance because their principal role is to generate informative infrastructure candidates and violated cuts. The tolerance is tightened when the certified LBBG gap approaches the current master accuracy, when the same infrastructure candidate reappears, or when progress stalls. For a finite certified gap, the implemented tightening rule can be summarized as follows.

$$\epsilon_{k+1}^{\text{MP}} = \max \left\{ \epsilon_{\min}^{\text{MP}}, \min \left\{ \rho_{\text{MP}} \epsilon_k^{\text{MP}}, \max \left\{ \epsilon_{\min}^{\text{MP}}, \frac{\text{Gap}^{(k)}}{2} \right\} \right\} \right\}, \quad (65)$$

where, $0 < \rho_{\text{MP}} < 1$, whenever a tightening trigger is activated. If no finite certified gap is yet available, only the multiplicative reduction is applied. The minimum master tolerance $\epsilon_{\min}^{\text{MP}}$ is selected sufficiently tightly relative to ϵ_{LBBG} . Adaptive master accuracy is an implementation level convergence control mechanism rather than a modification of the underlying LBBG bounds. Gurobi's master MIP gap determines when the current master solve may terminate relative to its incumbent and best bound, while the outer LBBG gap in Eq. (56) determines algorithmic convergence. The master solver best bound remains valid even when the temporary master incumbent has not been proven optimal.

Candidate caching and repeated-evaluation control. Infrastructure configurations are identified by deterministic signatures containing all charger, PV, and BESS counts. The cache stores feasible objectives, solver bounds, and fixed-MIP gaps to avoid repeated evaluation of unchanged infrastructure. If a cached configuration persists at the minimum master tolerance without producing an additional separating cut, the run terminates with a stagnation status. Stagnation is reported separately and does not satisfy the certified stopping criterion in Eq. (57). Optional continuous-master initialization and infrastructure repair generate candidates only; each candidate must be certified by the exact annual MIP before updating the feasible lower bound.

Accepted inference cuts make the final master dimensions run-dependent. Table 5 distinguishes the initial master from exact operational certification.

Appendix B. Computational performance and scalability

The full city-scale instance assesses matrix size and observed resource use. A reduced instance supports cross-method validation and repeated tolerance experiments under the same modeling structure.

B.1. Full-scale structural reduction and computational performance

The full instance uses 638 zones, twelve representative months, 48 intervals, three public charger types, and two demand classes. Its 1598 spatial arcs generate 472 800 active arc-slots and 186 768 component-slot values. Table 5 compares the structural representation and solver matrices of the monolithic formulation, the initial LBBG strategic master, and the fixed-infrastructure exact annual certification MIP. The dominant dimensional reduction arises from redirection. The exact monolithic formulation simultaneously represents $|\mathcal{A}|(|\mathcal{C}|^2 + 4) = 6\,146\,400$ type-aware and discrete redirection variables, whereas the strategic master retains only $|\mathcal{A}| = 472\,800$ aggregate arc-slot redirection variables. Consequently, 5 673 600 exact redirection variables are deferred from the strategic master, corresponding to a 92.3% reduction in this block. The $|\mathcal{A}||\mathcal{C}|^2$ term therefore describes the structural growth of the type-pair representation rather than the computational complexity of solving the MILP. At the complete initial solver-matrix level, the LBBG master contains 54.9% fewer rows, 60.1% fewer columns, and 72.9% fewer nonzero coefficients than the monolithic formulation. Its binary and non-binary integer variable counts are reduced by 97.9% and 99.3%, respectively. For the maximum recorded presolved master matrices, the corresponding reductions are 54.6%, 68.2%, and 66.5%. Exact type-pair and discrete operational relationships are subsequently restored only for fixed-infrastructure certification. The exact annual fixed-investment MIP retains a large initial matrix, while fixing investments enables stronger presolve in these runs: its maximum recorded presolved rows, columns, and nonzeros are 61.4%, 58.5%, and 60.0% lower, respectively, than the recorded presolved monolithic matrix. The master and certification matrices are solved sequentially and must not be interpreted as additive dimensions of a single optimization model.

The structural reductions do not imply lower computational effort for every component of the decomposition. The monolithic formulation required 100 008.9 s (27.78 h) of solver time in its single

Table 5

Full-scale structural and solver-matrix comparison of the monolithic MILP and the LBBB decomposition.

Metric	Monolithic MILP	LBBB master	Master reduction vs. monolithic (%)	Exact annual SP-MIP ^a
<i>Dominant redirection representation</i>				
Exact redirection variables	6146 400	472 800	92.3	6146 400
<i>Initial solver/model dimensions</i>				
Rows	11 483 106	5 177 678	54.9	11 483 106
Columns	12 772 030	5 098 153	60.1	12 768 841
Nonzeros	67 905 490	18 406 278	72.9	63 105 970
Continuous variables	11 455 752	5 077 081	55.6	–
Binary variables	840 288	17 882	97.9	–
Non-binary integer variables	475 990	3 190	99.3	–
<i>Presolved solver matrix</i>				
Rows	5 904 661	2 682 997	54.6	2 281 764
Columns	7 096 590	2 258 495	68.2	2 946 401
Nonzeros	29 765 033	9 969 195	66.5	11 891 779

The full instance contains 638 zones, 576 month-slot blocks, 472 800 active redirection arc-slots, and three public charger types. The reduction column compares the initial LBBB strategic master with the monolithic formulation. The monolithic redirection block contains $|A|(|C|^2 + 4) = 6\,146\,400$ exact redirection variables, whereas the strategic master retains only $|A| = 472\,800$ aggregate redirection variables and defers 5673 600 type-pair, activation, trip-count, and tail variables to operational evaluation. This is a structural dimensionality comparison, not an asymptotic bound on MILP solution time. Counts for the master and exact annual certification model refer to separate solver matrices and must not be summed.

^a The exact annual MIP fixes the infrastructure candidate selected by the master. Each reported matrix entry is the maximum for that metric across four certification calls. Three exact-configuration inference cuts, in addition to 156 bootstrap Hall cuts, were accepted in the reported full run.

main optimization, with 129 873.67 work units and 29 042 branch-and-bound nodes. Across nine strategic-master calls, LBBB accumulated 394 494.52 s (109.58 h) of master solver time, 481 775.78 work units, and 28 006 branch-and-bound nodes. In addition, six exact annual fixed-infrastructure certification MIPs required 55 871.68 s (15.52 h) in total, while seven linked annual LP evaluations required 5 840.76 s (1.62 h). The complete LBBB workflow required 469 449.50 s (130.40 h) end-to-end. These quantities have different measurement boundaries from the monolithic solver time and are therefore reported descriptively rather than as a direct end-to-end runtime ratio. The full-scale results consequently demonstrate a substantially smaller strategic optimization model and exact sequential operational certification, rather than a wall-clock speedup over the monolithic formulation.

The full-scale comparison therefore supports structural scalability rather than universal runtime dominance. LBBB substantially reduces the dimension and discrete content of the repeatedly optimized strategic problem, while exact type-aware operational relationships are recovered sequentially through fixed-infrastructure certification. The computational trade-off is additional decomposition and certification effort in exchange for a markedly smaller strategic search space.

B.2. Reduced benchmark for cross-method validation

A reduced benchmark is used to complement the full-scale structural assessment. It retains the same spatial, temporal, charger, PV-BESS, and user-redirection modeling logic while permitting repeated controlled solution of all three implemented workflows. Its purpose is to verify agreement in the objective and strategic decisions and to distinguish the computational behavior of the direct monolithic MILP, the arc-witness Benders decomposition, and LBBB. The reduced case is therefore interpreted as a formulation-validation experiment rather than as a substitute for the full city-scale computational assessment.

Table 6 shows objective deviations below 0.0004% and identical aggregate charger counts across the three workflows. Relative to the monolithic solution, LBBB differs by +0.0265% in PV panels, −0.3115% in BESS units, +0.0957% in redirected demand, and −0.0034% in grid procurement. These differences are consistent with near-equivalent solutions. Equal charger totals do not by themselves establish identical zone-level deployment.

Fig. 13 compares solution agreement with computational burden. Despite its smaller initial matrix, the implemented Benders comparator uses 42.70× the monolithic primary solver work. LBBB reduces

initial rows, columns, and nonzeros by approximately 62.0%, 65.2%, and 77.9%, respectively, but takes longer than the monolithic solve. Primary solver work describes the reported solver calls and should be distinguished from total workflow runtime. The implemented Benders comparator retains discrete redirection witnesses in its master and evaluates continuous operational LP recourse, as documented in the public repository. LBBB transfers more discrete operational logic to fixed-infrastructure evaluations, reducing the primary mixed-integer model and observed effort relative to this comparator.

The reduced benchmark supports numerical consistency, while both tested scales show approximately 19% lower LBBB peak RSS than the monolithic workflow. They do not establish that the relative memory advantage increases with instance size. The structural reduction follows from the master/recourse partition; broader memory and runtime scaling requires matched measurements at additional sizes.

Appendix C. Numerical tolerance sensitivity on the reduced benchmark

Following the cross-method validation, the reduced benchmark is used to assess the numerical sensitivity of the LBBB stopping criterion. This experiment isolates the effect of the requested outer optimality gap while retaining the same spatial, temporal, charger, PV-BESS, and user-redirection modeling structure. The reduced case permits repeated controlled experiments at substantially lower computational cost than the full city-scale instance and should therefore be interpreted as a numerical-certification sensitivity analysis rather than as an additional scalability experiment.

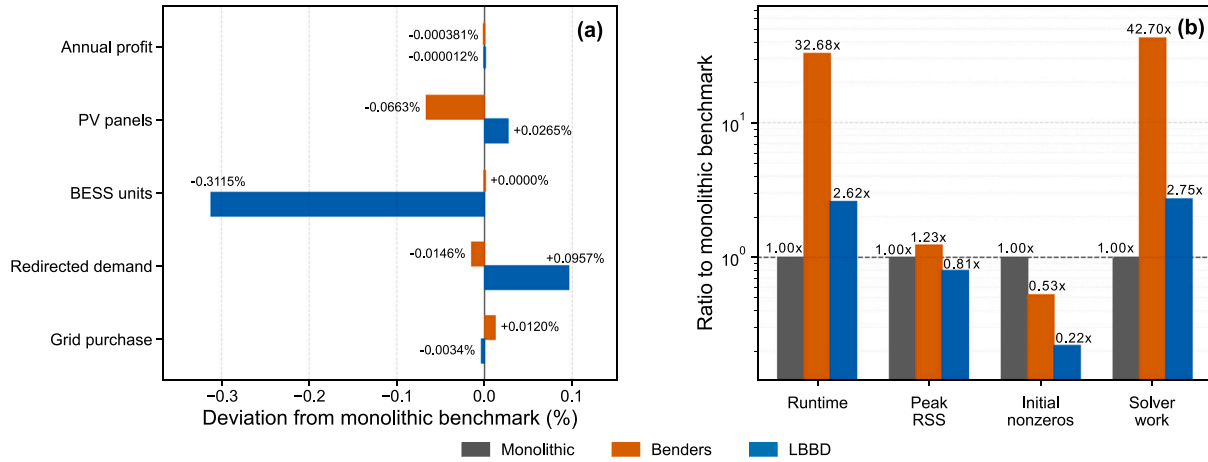
Sensitivity to the outer LBBB tolerance. The outer gap measures the interval between the global upper bound and best certified feasible lower bound using Eq. (56). The tested targets are 0.0100%, 0.0050%, 0.0025%, and 0.0010% (Table 7). The first three targets were attained. Tightening the target from 0.0100% to 0.0025% reduced the certified gap approximately 5.6-fold and the bound width from approximately SEK 11,491 to SEK 2,053. Across the runs, best feasible profit varied by 0.002769%, all selected 72 slow, 402 medium, and 41 fast chargers, and unmet demand was zero to numerical precision.

Fig. 14 shows convergence by iteration and elapsed time. The 0.0025% target achieved the tightest certificate under the tested controls. The 0.0010% target remained unmet after eight iterations, including cached candidates. A tighter requested tolerance therefore does

Table 6

Reduced-instance validation and computational comparison of the three optimization workflows.

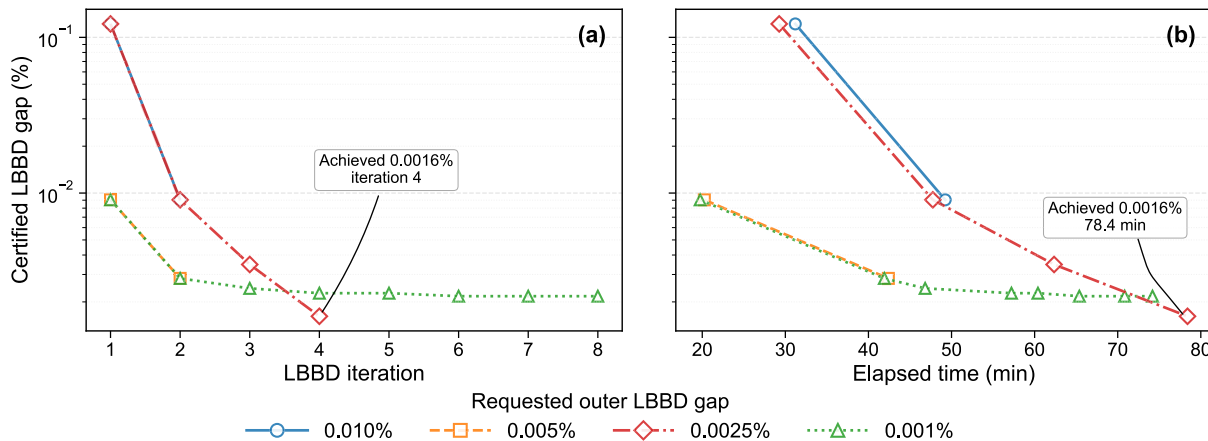
Metric	Monolithic	Benders	LBBD
Annual profit (MSEK/yr)	126.991946	126.991462	126.991931
Objective deviation from monolithic (%)	–	–0.000381	–0.000012
Slow chargers	72	72	72
Medium chargers	402	402	402
Fast chargers	41	41	41
Total runtime (min)	20.16	658.83	52.77
Runtime relative to monolithic	1.00×	32.68×	2.62×
Peak process-tree RSS (GiB)	25.17	30.89	20.29
Initial solver rows	1,189,599	1,276,066	452,493
Initial solver columns	1,340,745	1,019,913	466,011
Initial solver nonzeros	7,590,291	4,046,754	1,677,568
Primary solver work units	907.90	38,763.83	2493.20

**Fig. 13.** Reduced-instance comparison of the three optimization workflows: (a) deviations in selected solution and operational quantities relative to the monolithic benchmark and (b) computational metrics normalized by the corresponding monolithic values.**Table 7**

Sensitivity of the reduced-instance LBBD solution to the requested outer optimality gap.

Requested gap	Achieved gap	Target reached	Iterations	Runtime (minutes)	Δ Profit
0.0100%	0.009048%	Yes	2	50.08	-0.002769%
0.0050%	0.002831%	Yes	2	43.26	-0.000746%
0.0025%	0.001616%	Yes	4	79.44	0.000000%
0.0010%	0.002176%	No	8	75.07	-0.000578%

Δ Profit is relative to the best feasible profit among these four runs, obtained with the 0.0025% target. “Target reached” compares the achieved outer gap with the requested value; it is separate from the status or gap of an individual Gurobi solve.

**Fig. 14.** Sensitivity of LBBD convergence to the requested outer optimality gap on the reduced benchmark: (a) certified gap by LBBD iteration and (b) certified gap by elapsed decomposition time. The vertical axis is logarithmic.

not guarantee a tighter achieved certificate when inner solves and repeated-candidate handling are unchanged. Runtime need not vary monotonically across individual mixed-integer runs.

Data availability

The optimization implementation, a reduced Gothenburg test instance, and solution outputs are publicly available in a GitHub repository. The repository contains the direct monolithic MILP, Benders, and LBBDD workflows together with reduced-instance comparison utilities and run outputs used for reproducibility and computational validation. The full processed Gothenburg region case study inputs used for the reported numerical analysis are available from the authors upon request.

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