

Article

A Rolling-Horizon Model Predictive Control Energy Management System for Shaping the Ports of the Future

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Highlights

What are the main findings?

- A rolling-horizon MPC-MILP EMS is evaluated over a full 8760 h year for a real smart-port energy hub.
- Anticipatory control shifts the BESS from reactive backup behaviour to active price-arbitrage operation.
- MPC raises mean BESS SoC from 13.6 percent to 46.0 percent and reduces minimum SoC residence from 81 percent to 6 percent.

What are the implications of the main findings?

- The key decarbonisation-enabling asset is not the BESS alone but the BESS–EMS pair.
- A reproducible workflow supports replication across comparable port, campus, district, and prosumer energy hubs.

Abstract

Smart-port decarbonisation requires operations-research decision support under day-ahead uncertainty. We present a rolling-horizon Model Predictive Control Energy Management System, formulated as a Mixed-Integer Linear Program with five forecast streams, and benchmark it against a deterministic rule-based controller on an identical configuration. A full-year proof-of-concept at the Port of Ancona (8760 hourly steps over the 2024 Italian Day-Ahead Market, 6.5 MWp PV, 1.0 MWh BESS) combines realised 2024 market, photovoltaic and auxiliary-demand series with a post-AFIR projected cold-ironing demand—the dominant load—and is therefore an operational proof-of-concept rather than a fully metered baseline. The principal MPC outcome is structural: anticipatory dispatch raises the mean BESS state of charge from 13.6% to 46.0% and cuts residence at the minimum SoC from 81% to 6% of hours. The forecasting layer attains sub-7% sMAPE on cold-ironing-loaded demand and 9–18% on the remaining streams (seasonal MASE₂₄ ≤ 0.74 on demand and price streams). At the relay-constrained 0.08 C pilot, the realised savings is 0.44% (€14,463 yr⁻¹; 95% moving-block bootstrap CI [€12,842, €15,742]); benchmarked against an enhanced rule-based controller that is itself permitted price-threshold grid charging, the residual value of predictive optimisation is €5652 yr⁻¹ (0.17%), with the remainder of the gap being the value of enabling grid charging. A C-rate sweep shows the savings doubling to 0.93% at 0.5 C, and a direct 20 MWh/±10 MW simulation yields a €0.57 M yr⁻¹ gross arbitrage savings whose net value, after a realistic battery-degradation penalty, is substantially smaller. Controller-level operational CO₂ rises marginally (+6.2 t,

Academic Editor: Pierluigi Siano

Received: 16 May 2026

Revised: 12 June 2026

Accepted: 25 June 2026

Published: 30 June 2026

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+0.13%), an effect distinct from—and dwarfed by—the system-level cold-ironing decarbonisation. The framework is reproducible in open-source Python (PuLP/HiGHS) from the actual data and is portable to other single-node smart city energy hubs.

Keywords: smart ports; smart cities; cold ironing; model predictive control; mixed-integer linear programming; battery energy storage; Adriatic–Ionian

1. Introduction

Seaports aggregate high-power industrial loads, pulse-like vessel-side cold-ironing (CI) demand, embedded renewable generation and a permanent grid connection under unified port authority control [1–3]; the smart-port concept enters the smart city energy management corpus once the focus shifts to coordinating these flows under day-ahead market uncertainty [4,5]. Three EU instruments compel European port authorities to deploy CI at TEN-T core ports from 1 January 2030, integrate renewables, and operate the resulting microgrid cost-effectively: AFIR Article 9 [6], FuelEU Maritime Article 6 [7] and ETS-maritime [8] (Article-level specifications in §3.1.4) [9].

The operational translation is under-developed at the individual port level. Two disconnected bodies of work coexist: techno-economic profiles of individual port-energy components, namely, shore-power [10,11], port PV [12,13], hybrid renewables [2,3,14] and BESS sizing [15,16]; and rolling-horizon MPC/MILP dispatch on stylised microgrids [17–19]. Bringing the two together at a named port, with empirically grounded forecasting and a controlled comparison against a reactive baseline, is the gap addressed here. The framework was developed within a regional smart-port energy management project and is documented in its supporting deliverable [20].

The MILP-MPC choice over RL is deliberate: linear objective and dynamics, the only non-convexity is binary charge–discharge exclusivity, so the MILP returns a guaranteed global optimum with shadow-price duals at every solve [21,22]; Section 5.4 develops the OR framing and RL comparison [23]. Predictive energy management is the central lever across the wider energy-systems literature—from microgrid dispatch to electrified transport [24,25]—but its operational value at a named smart port, isolated from confounding modelling choices, has not been quantified. Against the comparator literature ([19] Omega, [18] Energies, [26] IEEE TCST, the nZEP line [2–4,27–29]), the sharpened contribution is fourfold: (i) a full-year hourly evaluation on realised 2024 CNOR Day-Ahead prices—combining realised market, PV and auxiliary-demand series with a post-AFIR projected cold-ironing load—end-to-end traceable from the forecast and realised input data to every table and figure; (ii) a controlled comparison that, under strict operational equivalence, decomposes the rule-based gap into the value of permitting grid charging ($\approx 61\%$) and the residual value of predictive optimisation ($\approx 39\%$), instead of reporting a single conflated saving; (iii) a C-rate and capacity sweep that, together with shadow-price duals, diagnoses the binding resource at the pilot as power, not energy capacity; and (iv) statistically rigorous reporting (moving-block bootstrap 95% CI; DM-HAC test) over a reproducible data contract that anchors a single-node-hub transferability claim in structural versus economic decoupling. Section 2 reviews the literatures, Section 3 develops the framework, Section 4 reports the Port of Ancona results, Section 5 discusses implications and limitations, and Section 6 concludes the paper.

2. State of the Art

2.1. Smart Cities, Smart Ports and the Energy-Systems Thread

The smart cities literature has progressively absorbed an energy-and-decarbonisation thread driven by distributed generation and storage [1,30]. Bibri-Krogstie position energy management as a horizontal capability across six functional domains (governance, economy, mobility, environment, people, and living) [1]; Bellini et al. organise the IoT smart city thread around a five-layer sensing–communication–data–analytics–presentation architecture [30]. Ports operate as concentrated micro smart cities with identifiable demand profiles, port authority control and dense digital instrumentation (AIS, smart metering, environmental sensors) [31–33]; Yau et al. distinguish five port-side technology layers (sensors, networks, computing, analytics, and decision support) [32]. Molavi-Lim-Race aggregate technical, operational and environmental dimensions into an indexing framework [5,34], with Buiza et al. providing the Mediterranean baseline [35]. The smart-port architecture is well-mapped; however, the operational dispatch problem is not.

2.2. Cold Ironing, Shore-Power Deployment and Port-Microgrid Energy Management

The CI literature matured under AFIR/ETS-maritime regulatory pressure: Innes-Monios document the small–medium-port retrofit challenge [10,36]; European-wide rollout is estimated at >0.5 Mt CO₂eq/yr under full AFIR [37], with CI vs. LNG assessments [38] and onshore-power adoption economics [39]. Iris-Lam catalogue operational levers (CI, energy-efficient cranes, LED retrofit) [11] and formalise the seaport smart-grid EMS problem [19]; Misra et al. [12], Hein et al. [13,40] and Wang et al. [14] extend to GHG accounting, all-electric vessels with onboard PV, and two-stage HRES. The nearly Zero Energy Port (nZEP) typology of Sifakis et al. is the organising Mediterranean/Adriatic reference [2–4,41], extended by CI-PV temporal coupling [28], resilient HRES sizing [29] and Mediterranean implementation roadmap [27]. The operational dispatch problem, distinct from sizing, has received less attention [42,43]; this is the gap addressed here.

2.3. Model Predictive Control and Mixed-Integer Linear Program for Microgrid Dispatch

The microgrid literature has converged on rolling-horizon MPC-MILP for systems with battery storage, dispatchable loads and grid interaction [17,18,26,44,45] across four themes: canonical formulations with unit-commitment binaries [26]; two-stage/hierarchical extensions [17,46,47]; grid-connected MILP-EMS [18]; and risk-aware/hydrogen-storage formulations [44]. Model-based MILP-MPC retains an interpretability advantage over data-driven economic MPC [48], suitable for port authority auditability demands (Section 5.4). Reported MPC vs. RB savings span 5–15%, with the magnitude correlated to price volatility [18,19,26]. RL is complementary where the explicit MILP model is incomplete or non-stationary [23]; MILP retains guaranteed optimality, interpretability and dual-signal extraction. The same predictive control principle underpins energy management well beyond stationary microgrids—recent work applies predictive and learning-based strategies to MW-class parallel hybrid-electric aircraft propulsion [24] and to real-time, multi-objective fuel-cell-vehicle energy management [25]—which underscores the generality of anticipatory dispatch; what remains scarce is its named-port, full-year evaluation against real DAM prices.

2.4. Forecasting for Energy Systems

Day-ahead price and load forecasting use gradient-boosting, LSTM and transformer models reporting sMAPE 5–15% on liberalised European markets [49–51] and 3–10% for hourly building loads [52,53]. PV forecasting combines clear-sky models with weather correction [54–56]. CI demand is structurally distinct from autocorrelated building or microgrid

loads: vessel arrivals are pre-announced via harbour-master and AIS [57], so timing is deterministic, whereas in-connection power depends on vessel typology, operational mode and shore-supply standards. The Section 3.5 architecture is calibrated to these signatures.

2.5. Research Gap and Contribution

Four structural gaps motivate this contribution. (i) A full-year, hourly-resolution, named-port MILP-MPC evaluation against real DAM data—here combining realised 2024 market, PV and auxiliary-demand series with a projected post-AFIR cold-ironing load—is absent. (ii) Controlled MPC versus rule-based comparisons are rarely instrumented at the level of operational equivalence and, to our knowledge, never decomposed into the value of grid-charging permission versus the value of predictive optimisation proper. (iii) The dual apparatus that translates dispatch outputs into governance/investment signals (shadow prices on BESS capacity, grid limits, CI demand) is not exposed by published port-EMS studies, despite being routine in smart city decision-support frameworks [41,58]; we extract these duals and use them to identify the binding resource at the pilot scale. (iv) Reproducible, open-source EMS implementations are rare. The framework developed here addresses all four gaps over 8760 hourly steps of realised 2024 CNOR DAM prices and is implemented in open-source Python (PuLP/HiGHS) [20,59].

3. Materials and Methods

Notation: t (operational hour, 1–8760); H (horizon length, 24 h); Δt (time step, 1 h); P_{PV} , P_{load} , P_{ch} , P_{dis} , P_{imp} , P_{exp} (PV, load, charge, discharge, grid-import and grid-export powers, kW); $u(t) \in \{0, 1\}$ (BESS mode binary); SoC (state of charge); E_{BESS} (BESS capacity, kWh); η_{ch} , η_{dis} (charge/discharge efficiencies); c_{buy} , c_{sell} (grid purchase/sale prices, EUR/kWh).

3.1. Case Study: The Port of Ancona as a Smart Maritime Cluster (Post-AFIR Cold-Ironing Scenario)

The Port of Ancona (43.62° N, 13.50° E) is the lead pilot site of this study: the principal commercial seaport of the Marche region, the gateway between Italy and the Western Balkans, and a TEN-T core-network port subject to AFIR shore-power from 1 January 2030 [6]. ADSPMAC administers a heterogeneous traffic mix [20] (Ro-Ro ferries on year-round Adriatic routes, seasonal cruise traffic in Apr–Oct, container feeder, dry/liquid-bulk general cargo, tug/pilot/harbour-service craft). Under full AFIR deployment to the five passenger/Ro-Ro quays (mid-2026 target), the pilot assumes an annual CI energy of 19.97 GWh (a post-AFIR projection, not a 2024 metered baseline). Auxiliary loads contribute ≈ 9.97 GWh/yr with a smooth diurnal-weekly profile. Combined demand ≈ 29.9 GWh/yr exceeds on-site PV (≈ 8.99 GWh/yr from 6.524 MWp) by a factor of 3.3, so the port remains a net importer. Eight site-specific characteristics (Table 1) motivate the selection: regulatory exposure, strategic position [60], traffic heterogeneity, renewable resource, market structure, data access, replication potential and infrastructure scale.

Table 1. Eight site-selection criteria for the Port of Ancona as the lead pilot site.

#	Criterion	Justification at Ancona
(i)	Regulatory exposure	TEN-T core-network port, first AFIR-cohort, 2030 mandate [6].
(ii)	Strategic position (Adriatic–Ionian)	Central node within the regional Adriatic–Ionian port network.
(iii)	Mixed traffic profile	Ferries + cruise + container + general cargo, covering the full range of CI demand structures.

(iv)	Climate/PV resource	$\approx 1378 \text{ kWh}\cdot\text{kWp}^{-1}\cdot\text{yr}^{-1}$ realised yield; regional wind/wave assessments [60].
(v)	Italian DAM (IPEX/GME)	Clears $\sim 15:00$ for next 24 h, matching the EMS rolling horizon.
(vi)	Port authority data access	The port authority provides harbour-master, metering and operational data access.
(vii)	Replication potential	Follower ports Split (HR) and AD Marina Bar (ME) share Adriatic location, mixed traffic and scale.
(viii)	Mid-size scale	Large enough for the full five-stream MPC; representative of the broader Mediterranean port population.

3.1.1. Multi-Dimensional Characterisation

Figure 1 characterises the case study across the spatial, temporal, energy, market and operational dimensions via a 4×4 composite sourced 100% from realised 2024 time series and aggregated actual data.

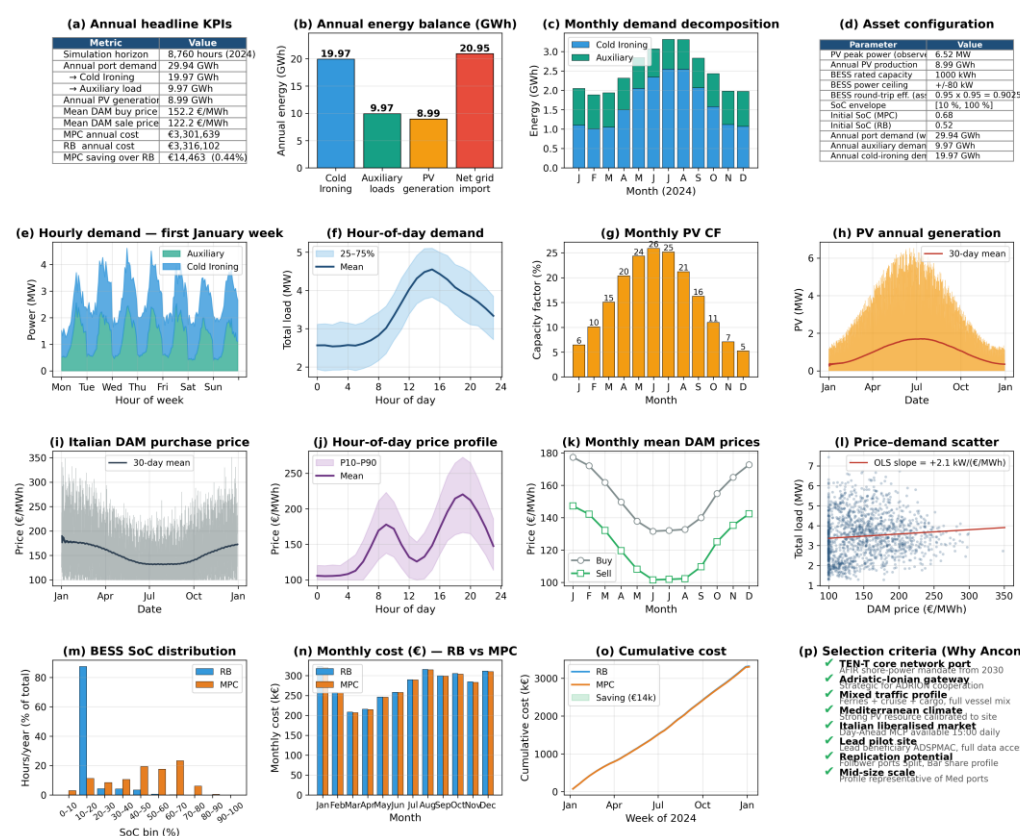


Figure 1. Port of Ancona case study, 4×4 composite. Row 1: site/asset configuration (annual KPIs, GWh energy balance, monthly stacked demand, asset table). Row 2: demand and PV structure (representative week stacked demand, hour-of-day demand profile with 25–75% envelope, monthly PV capacity factor, annual PV with 30-day rolling mean). Row 3: market (annual DAM purchase price trajectory, hour-of-day P10–P90 envelope, monthly mean buy/sell, DAM vs. load scatter). Row 4: controller diagnostics (SoC histogram MPC vs. RB, monthly cost, weekly cumulative cost with running savings, eight Ancona selection criteria).

Three structural facts emerge. CI demand is temporally non-stationary on every observable scale (Ro-Ro pulses, cruise-driven summer concentration, daily-granularity arrivals); a controller that does not anticipate these patterns dispatches the BESS reactively against demand events whose arrival is already known. The PV resource is seasonally complementary to the auxiliary load and partially complementary to ferry-driven CI; the storage

question is whether the BESS shifts the diurnal mismatch between the daytime PV peak and the evening departure peak. The DAM price exhibits a P10–P90 inter-decile range exceeding €60/MWh at peak hours, creating a substantial price-arbitrage opportunity.

3.1.2. Regulatory Framing

AFIR Article 9 [6] mandates OPS at TEN-T core ports from 1 January 2030 for container ships ≥ 400 GT with ≥ 50 annual calls and passenger ships ≥ 400 GT with ≥ 25 calls. FuelEU Maritime Article 6 [7] requires OPS or zero-emission technology for these vessel classes berthed > 2 h, with progressive fuel carbon-intensity limits. EU ETS maritime [8] phases allowance surrender at 40%/70%/100% for 2024/2025/2026 reporting years. AD-SPMAC's pre-emptive retrofit places Ancona ahead of the 2030 deadline; the EMS reported here operates on the post-AFIR demand profile.

3.2. Physical System Configuration

The physical system (Figure 2) comprises five subsystems within the port boundary. (i) PV generator: 6.524 MWp rooftop and ground-mounted array, south-facing 35° tilt, realised 2024 yield ≈ 1378 kWh/kWp/yr from the Renewables Ninja platform [55] $\rightarrow \approx 8.99$ GWh/yr ($\approx 30\%$ of total demand). (ii) BESS: 1.0 MWh LFP rated ± 80 kW, SoC envelope [10%, 100%], round-trip efficiency $\eta_{ch} \cdot \eta_{dis} = 0.95 \times 0.95 = 0.9025$. The 0.08 C-rate of this deployable pilot is constrained by the existing distribution-board protection relay; a planned retrofit will commission a 0.5 C protection scheme. (iii) CI load: 19.97 GWh/yr post-AFIR projection, provisioned entirely per IEC/IEEE 80005-1:2019 (HVSC) [61] at the AFIR-mandated passenger, Ro-Ro and cruise quays (6.6 or 11 kV, 50 Hz landside), because AFIR Article 9 applies to vessels ≥ 400 GT (all > 1 MVA). IEC/IEEE 80005-3:2014 (LVSC) [62] is the reference for sub-1-MVA harbour-service connections (negligible contribution to the 19.97 GWh aggregate). (iv) Auxiliary loads: cranes, refrigeration, lighting, offices, pumping ≈ 9.97 GWh/yr, smooth diurnal-weekly profile. (v) Grid connection: ± 30 MW bidirectional, deliberately non-binding to isolate BESS scheduling from grid-capacity artefacts; round-trip efficiency captures power-electronic losses via the η -product above.

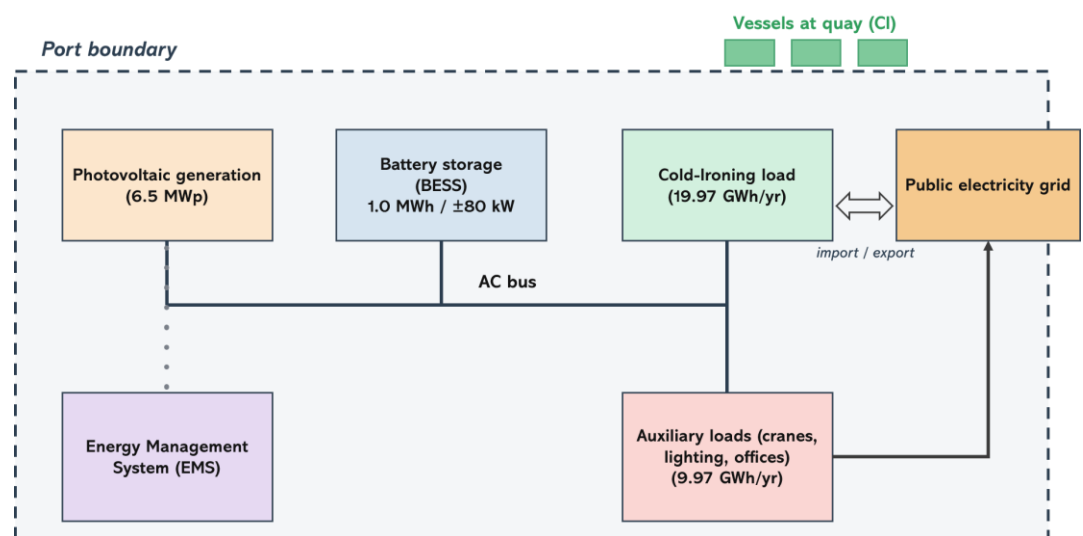


Figure 2. Port-microgrid configuration (Port of Ancona). PV, BESS, CI and auxiliary loads share a common AC bus; bidirectional ± 30 MW grid connection; the EMS supervises BESS dispatch and grid interaction.

3.3. EMS Architecture

The EMS instantiates Layer 4 of the Yau et al. smart-port stack [32] and the Bellini et al. IoT smart city stack [30], complementary to Bibri-Krogstie's six functional domains [1]. L1 Acquisition: smart meters at CI quays, BESS converter and grid-feed (1 s sampling, 1 min Modbus TCP); pyranometer, temperature and wind sensors; PLCs for BESS dispatch; AIS via public feed plus ADSPMAC harbour-master scheduling. L2 Communication: fibre to core assets, 5G/LoRaWAN to dispersed equipment, MQTT + OPC-UA. L3 Data Management: InfluxDB + PostgreSQL with cleaning pipeline. L4 Analytics: five-stream forecasting suite (Section 3.5) feeding the MILP (Section 3.4). L5 Presentation: role-specific dashboards with alerts. Design targets (50 KB/s aggregate L1–L3, 50 ms BESS-edge, 10 ms core-asset fibre, 5 min dashboard refresh) are indicative [20] and pending operational verification.

3.4. Rolling-Horizon MILP Formulation

The EMS minimises the total electricity procurement cost over the planning horizon. Following the canonical microgrid-MPC formulation [17,26], at each hour t , the EMS solves a 24-step MILP and applies the first time-step decision before advancing the horizon by $\Delta t = 1$ h. The objective function is

$$\min \sum_{\tau=t}^{t+H-1} [c_b(\tau) \cdot P_i(\tau) - c_s(\tau) \cdot P_e(\tau)] \cdot \Delta t \quad (1)$$

subject to the power balance at the port AC bus,

$$P_{PV}(\tau) + P_i(\tau) + P_d(\tau) = P_L(\tau) + P_e(\tau) + P_c(\tau) \quad (2)$$

the BESS energy balance dynamics,

$$S(\tau + 1) = S(\tau) + \frac{\eta_c \cdot P_c(\tau) - P_d(\tau) / \eta_d}{E_B} \cdot \Delta t \quad (3)$$

state-of-charge bounds,

$$S_{min} \leq S(\tau) \leq S_{max} \quad (4)$$

charge/discharge power bounds with binary mutual exclusivity,

$$0 \leq P_c(\tau) \leq u(\tau) \cdot P_{c,max}, 0 \leq P_d(\tau) \leq (1 - u(\tau)) \cdot P_{d,max}, u(\tau) \in \{0,1\} \quad (5)$$

and grid import/export bounds,

$$0 \leq P_i(\tau) \leq P_{i,max}, 0 \leq P_e(\tau) \leq P_{e,max} \quad (6)$$

The integrality constraint on $u(\tau)$ prevents the LP relaxation from constructing infeasible simultaneous charge/discharge cycles. The grid import/export pair in Equation (6) is *not* constrained by a complementary binary because under $c_{buy}(\tau) > c_{sell}(\tau)$ on every realised hour (0 of 8760 h with $c_{buy} \leq c_{sell}$; minimum spread 7.79 EUR/MWh), simultaneous import-and-export is naturally suppressed. The realised dispatch confirms this: 0 h of simultaneous $P_{imp}(\tau) > 0$ and $P_{exp}(\tau) > 0$ under both MPC and the rule-based controller. The configuration parameters are listed in Table 2; the ± 30 MW grid limits are deliberately non-binding (peak combined load + PV ≈ 13 MW).

Table 2 lists the deployable specification (1 MWh/ ± 80 kW, 6.5 MWp PV, 30 GWh demand). The 0.08 C-rate is well below typical practice (0.5–1 C [15,16]) because the BESS power rating is constrained by the existing distribution-board protection relay [20]; a planned retrofit will commission a 0.5 C scheme. This ± 80 kW ceiling is the dominant economic constraint at the pilot: it limits the rate at which the BESS can absorb PV surplus, buffer cold-ironing pulses and arbitrage intraday price spreads, and it therefore partly explains the modest realised savings (Section 4.3). To quantify its effect, we re-run the identical full-year MPC and rule-based controllers at 0.5 C (± 500 kW) and 1.0 C (± 1000 kW) on the same 1 MWh pack; the resulting C-rate sensitivity is reported in Section 4.3. The Section 5.7 scaling argument connects this configuration to a 20 MWh/ ± 10 MW target state.

Table 2. EMS configuration parameters for the Port of Ancona proof-of-concept simulation (pilot configuration, 2024).

Parameter	Value	Units
BESS rated capacity E_{BESS}	1000	kWh
Minimum state of charge SoC_{min}	10	%
Maximum state of charge SoC_{max}	100	%
Charge power ceiling $P_{ch,max}$	80	kW
Discharge power ceiling $P_{dis,max}$	80	kW
Charging efficiency η_{ch}	95	%
Discharging efficiency η_{dis}	95	%
Grid import limit $P_{imp,max}$	30,000	kW
Grid export limit $P_{exp,max}$	30,000	kW
Initial state of charge $SoC(0)$	60 ² (both controllers)	%
Photovoltaic peak power	6524	kWp
Rolling-horizon length H	24	h
Time step Δt	1	h
Simulation horizon	8760 ¹ (1 January–30 December 2024)	h

¹ 2024 is a leap year (8784 h). The receding-horizon controller requires a full 24 h forward window, so the last solvable step begins 24 h before the data end; the dispatch therefore spans 8760 steps (1 Jan 00:00–30 Dec 23:00). ² Both controllers are initialised at $SoC(0) = 60\%$. The previously reported first logged states differ only because they correspond to the post-first-hour state after the first controller action, not to different initial conditions.

All Section 4 cost and SoC percentages are computed over these 8760 dispatch hours (normalised by the rule-based total over the same window), and the moving-block bootstrap resamples them; the omitted 24 h are <0.3% of the year. The forecast accuracy metrics presented in Section 4.4, which are independent of dispatch, use all 8784 forecast/actual pairs. Both controllers initialise at $*SoC(0)^* = 60\%$ (identical stored energy at $*t^* = 0$). The divergent first-logged states quoted in earlier drafts (68% MPC, 52% rule-based) were the $*post-first-hour^*$ values, differing only because the MPC charged and the rule-based controller discharged during hour 1; strict operational equivalence therefore holds (Section 3.7).

3.5. Forecasting Modules

Five forecast streams feed the MILP (Table 3). Grid purchase price: published day-ahead MCP plus Histogram Gradient Boosting trained out-of-sample on CNOR DAM 2015–2023 and evaluated on 2024 data [49,53]; hyperparameters via 5-fold expanding-window CV within 2015–2023; both models inherit the post-2022 crisis distribution shift (L5, Section 5.8). Grid sale price: the realised 2024 day-ahead market sale price (mean 0.122 €/kWh, range 0.044–0.326 €/kWh; there are no zero-price periods), forecast over the optimisation horizon and evaluated against the realised series (sMAPE 13.4%). PV generation: clear-sky with weather correction [54], validated against Renewables Ninja [55]. Port demand: auxiliary via regression with weather features [52]; CI via harbour-master + AIS schedule lookup [57] with first-arrival 75%-of-rated-CI (EMEP/EEA 2023 60–80% for cruise/Ro-Ro [63]), then vessel-specific profiles. A ± 10 pp shift in the 75% assumption shifts the annual CI by ± 1.3 GWh; under the Section 5.7 linear regime, the headline savings is expected to shift by $<\pm 5\%$, with a future metered campaign closing this loop. Weather: Open-Meteo Archive API.

Table 3. Forecasting module specifications for the five EMS input streams.

Stream	Model Class	Training Horizon	Exogenous Features	Hyperparameter Tuning	Data Source
Grid purchase price	Hist. Gradient Boosting [53] + published DAM	CNOR DAM 2015–2023 (8 y)	Hour, day, month, holiday	5-fold expanding-window CV	GME/IPEX
Grid sale price	Day-ahead market forecast	CNOR DAM 2015–2023	Hour, day, month, holiday	5-fold expanding-window CV	GME/IPEX
Photovoltaic generation	Clear-sky + weather correction [54]	n/a	Irradiance, temperature	n/a	Renewables Ninja [55]
Port demand (auxiliary)	Regression w/weather [52]	1 y metered	Temperature, irradiance, hour	scikit-learn ridge w/CV reg.	Port metering
Port demand (CI)	Vessel-DB schedule lookup + 75%–MCR cold start [63]	Vessel typology	Harbour-master + AIS [57]	n/a	ADSPMAC + AIS
Weather	Open-Meteo Archive (forecast horizon: 24 h)	n/a	n/a	n/a	Open-Meteo Archive API

The forecast accuracy realised by each module is reported in Section 4.4. To make explicit which inputs are known at the day-ahead decision time, which are genuine forecasts, what the optimiser is solved on, and what each forecast is evaluated against, Table 4 summarises the information status of every stream.

Table 4. Information status of each MILP input stream. Italian day-ahead prices clear at ~15:00 for the next 24 h and are therefore known at decision time; they are nonetheless treated here as forecasts, a deliberately conservative choice that propagates realistic price uncertainty into the dispatch. Realised values are used only to settle the executed first-step cost and to evaluate forecast accuracy.

Stream	Status at Decision Time (~15:00, D-1)	Treatment in This Study	Optimised on	Evaluated Against	sMAPE
Grid purchase price	Known (DAM MCP cleared)	Forecast (conservative)	Forecast	Realised DAM	9.2%
Grid sale price	Known (DAM)	Forecast	Forecast	Realised DAM	13.4%
PV generation	Forecast (weather-driven)	Forecast	Forecast	Realised PV	17.6%
Port demand (auxiliary)	Forecast	Forecast	Forecast	Realised metered	10.3%
Port demand (cold ironing)	Schedule known; berth power uncertain	Schedule lookup + 75%–MCR cold start	Forecast	Projected series ¹	6.8% ¹

¹ The cold-ironing stream is a post-AFIR *projection* (§3.1, §3.9), so its evaluation comparator is the projected series rather than a metered baseline; the 6.8% sMAPE is for the cold-ironing-loaded total demand, the highest-impact stream.

3.6. EMS Operational Cycle

At each hour t , the EMS executes the cycle of Figure 3: ingest 24 h forecasts, solve the MILP (1)–(6) over 24 steps, implement the first decision and advance by $\Delta t = 1$ h. The cycle is invariant across proof-of-concept (pre-stored data), real-time-offline (live advisory) and real-time-online (autonomous, human-supervised) modes. Recursive feasibility

is guaranteed (the inactive trajectory $P_{ch} = P_{dis} = 0$ is always feasible); closed-loop economic-MPC stability follows from Angeli–Amrit–Rawlings [64] and Rawlings–Mayne–Diehl [45,65]: under bounded forecast errors the closed-loop average cost is bounded by the open-loop optimum plus a forecast-error-variance term, with the Section 4.3 bootstrap as the empirical counterpart.

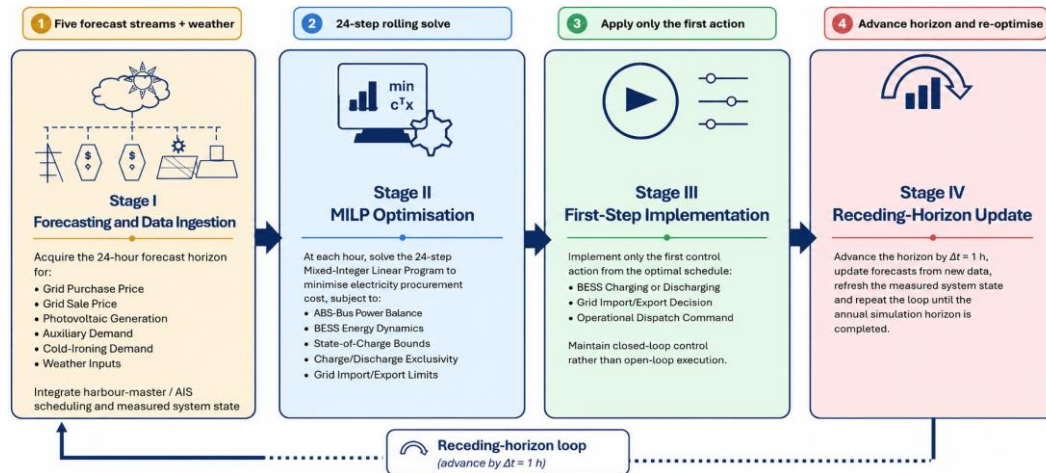


Figure 3. EMS operational cycle. At each hour: ingest 24 h forecasts → solve 24-step MILP → implement first decision → advance by $\Delta t = 1$ h.

3.7. Rule-Based Comparison Baseline

A deterministic rule-based EMS runs on an identical configuration, inputs and initial state: both controllers start at $SoC(0) = 60\%$, so the comparison begins from identical stored energy, and the only residual asymmetry is the no-grid-charging policy examined below (and with the Section 4.3 warm-up test). Four-step priority logic per hour: (i) PV to instantaneous load; (ii) PV surplus charges the BESS within bounds; (iii) load deficit discharges the BESS with cheap-tariff night-time logic; and (iv) PV surplus beyond load and BESS-charge exports. The η_{ch} , η_{dis} , SoC_{min} , SoC_{max} and grid limits are the same as the MILP, but there is no future information; each decision is locally feasible yet globally myopic.

Because this reactive baseline is forbidden from charging the BESS from the grid whereas the MPC may, part of the reported MPC advantage could reflect the value of permitting grid charging rather than of prediction itself. To separate the two effects, we add a second, enhanced rule-based comparator (RB⁺) that is permitted causal price-threshold grid charging using only past prices: it charges from the grid when the current purchase price is at or below the 25th percentile of the trailing 168 h and the SoC is below 80%, and it discharges to cover deficits when the price is at or above the trailing 75th percentile. RB⁺ is non-anticipatory by construction—it never uses future information—yet, unlike the reactive baseline, it is allowed grid arbitrage. The decomposition it enables (value of grid-charging permission versus value of predictive optimisation) is reported in Section 4.3 and discussed in Section 5.1.

3.8. Implementation

The EMS core uses Python 3.13 (NumPy 2.0, pandas 2.2, scikit-learn 1.x) with PuLP 2.9 over the HiGHS 1.7 solver [59]. Each 24-step MILP has ≈ 120 variables (96 continuous, 24 binary) and ≈ 120 constraints. The RNG seed is 20260514. PuLP/HiGHS was selected over Gurobi or CPLEX based on three criteria: open-source licence, performance parity at this scale (integrality gap closed at root in every solve), and audit traceability. All 8760 solves terminate ‘Optimal’; the full year runs in ≈ 5 min on standard CPU hardware (each 24-step solve completes in well under one second), so the controller operates comfortably

in real time on commodity equipment. The simulator reads ten input data series (five forecast and five actual streams); reproducibility is a single command-line invocation. The end-to-end procedure—data ingest, 24 h forecast assembly, MILP solve, first-step execution on actuals, state update and logging—is summarised in Figure 4.

The deployment footprint is correspondingly modest, which supports its practical feasibility. The optimisation runs on a single industrial PC or edge gateway; the supporting digital infrastructure is the Layer 1–3 stack of Section 3.3 (smart meters at the cold-ironing quays, the BESS converter and the grid feed; an MQTT/OPC-UA message bus; an InfluxDB/PostgreSQL historian), most of which is already required for AFIR metering and compliance reporting. The incremental cost of the control layer is therefore software integration and forecasting-model maintenance rather than new hardware, while the dominant capital item remains the BESS (LFP CapEx €250–400/kWh; Section 5.7). The computational burden is negligible relative to the metering and communication infrastructure a TEN-T port must deploy regardless.

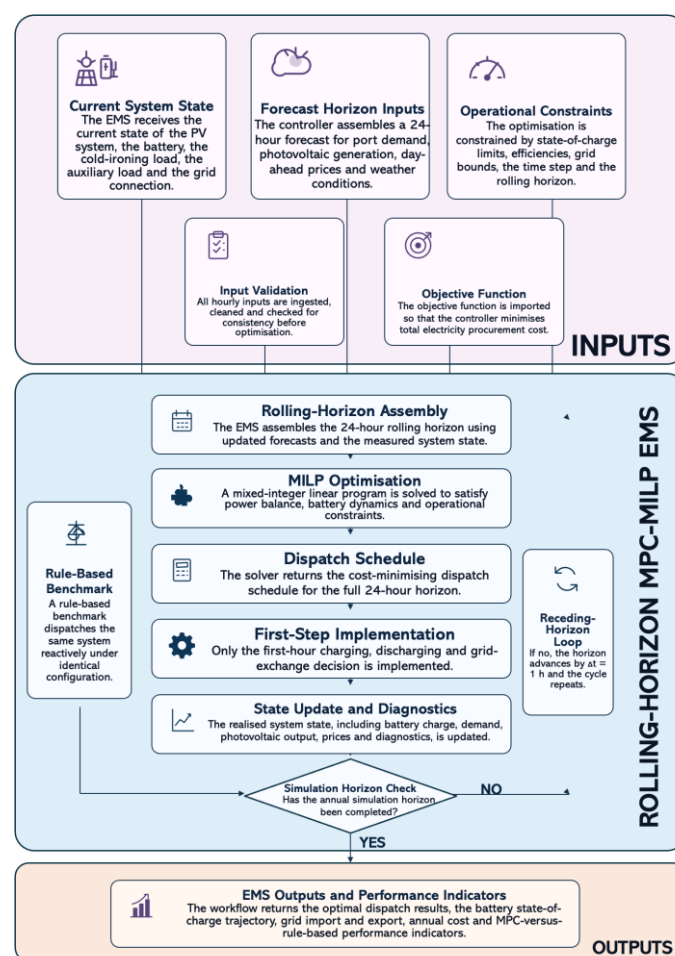


Figure 4. EMS operational flowchart: hourly data ingest → 24 h forecast assembly → 24-step MILP solve → first-step execution on actuals → state update and logging.

3.9. Assumptions

The proof-of-concept rests on the following explicit assumptions, several of which bound the interpretation of the results.

Case study. The Port of Ancona is modelled as a TEN-T core port under a post-AFIR projected demand regime (≈ 29.9 GWh/yr, of which 19.97 GWh is cold ironing), not its 2024 metered baseline; the cold-ironing stream—the dominant load—is therefore a projection (L1, Section 5.8).

Physical system. The hardware is fixed at a 6.524 MWp PV array and a 1.0 MWh/ ± 80 kW LFP BESS (round-trip $\eta^2 = 0.9025$, SoC $\in [10\%, 100\%]$) on a common AC bus behind a deliberately non-binding ± 30 MW grid connection.

MILP dispatch model. The controller minimises the hourly electricity procurement cost over a deterministic 24-step horizon with linear BESS dynamics, hard SoC bounds and mutually exclusive charge/discharge but no degradation, carbon or demand-charge term; the economic consequence of the degradation omission is quantified in Section 5.2.

Forecasting modules. Five point forecasts (gradient-boosting DAM purchase price, day-ahead forecast of the realised market sale price, clear-sky-plus-weather PV, ridge auxiliary demand, and an AIS/harbour-master schedule with a 75%-MCR cold start for cold ironing) are treated as the optimiser's inputs on a rolling 24 h horizon; the first step is then executed on realised actuals.

Rule-based baselines. The reactive comparator uses identical hardware, parameters and initial state as the MPC, but grid charging is forbidden; the enhanced comparator RB* is additionally permitted causal price-threshold grid charging (Section 3.7), so the two together separate the value of grid-charging permission from the value of prediction.

Statistical and uncertainty. All inferences use a moving-block bootstrap ($L = 168$ h, $B = 10,000$) and Diebold–Mariano with Newey–West HAC, interpreted strictly as within-year rearrangement variability over the single 2024 trajectory, not a multi-year confidence statement.

Economic and financial. Cash flows are limited to the hour-by-hour wholesale energy procurement net of export revenue; demand charges, ancillary-service payments, capacity remuneration and energy-community incentives are excluded and identified as the principal revenue-stacking extension (Section 5.7, R1). The 20 MWh target-state figure is a direct simulation of that configuration (Section 4.3, Section 5.7), not an extrapolation.

Environmental and emissions. Carbon is reported post hoc against the 2024 Italian average grid factor of 0.226 kg CO₂eq/kWh; embedded LFP emissions, marginal CCGT and AFIR-systemic NO_x/CO₂ displacement enter only as discussion brackets, never as MILP objectives. Controller-level and system-level carbon effects are reported separately (Section 4.3, Section 5.3).

Regulatory. AFIR Article 9, FuelEU Maritime Article 6 and the EU ETS-maritime 40%/70%/100% phase-in are assumed in force on schedule, with ADSPMAC's pre-emptive retrofit placing Ancona ahead of the 2030 deadline.

Smart cities positioning. The EMS is taken to occupy Layer 4 (analytics/decision-support) of the Yau–Bellini IoT smart city stack and to remain portable to other single-node hubs (campus, district-heat substation, EV-bus depot) given hourly metering, a volatile tariff and a non-trivially-sized BESS.

4. Results

4.1. Demand Forecasting

Annual demand decomposed into auxiliary and CI components is shown in Figure 5. Auxiliary load ≈ 9.97 GWh/yr (limited seasonality); CI load ≈ 19.97 GWh/yr (a post-AFIR projection, not a 2024 metered baseline; pre-AFIR Ancona CI is at most a fraction of a GWh) with pronounced ferry/cruise seasonality (Apr–Oct). Total demand ≈ 29.9 GWh exceeds PV (≈ 8.99 GWh from 6.524 MWp, yield ≈ 1378 kWh/kWp/yr) by a factor of 3.3, so the port is a net importer. The per-stream forecast accuracy on the five EMS streams is reported in Section 4.4.

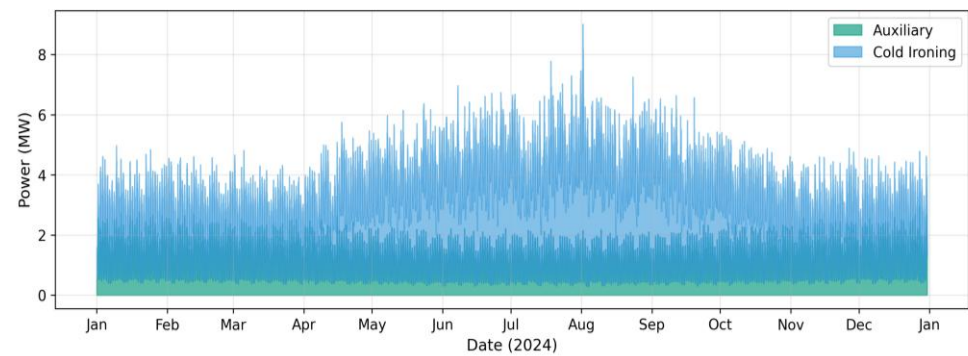


Figure 5. Annual port energy demand forecast: hourly CI and auxiliary across 2024.

4.2. EMS Dispatch Profile: MPC vs. Rule-Based

Under MPC (Figure 6), the BESS resides in mid-SoC bands for most of the year: mean annual SoC $\approx 46\%$, only 6% of hours at SoC_{min} , no meaningful residence at full charge under 2024 conditions. The MPC actively cycles the asset (Figure 7), sourcing charge from PV surplus and low-price grid hours, targeting discharge at peak-price and high-CI-demand episodes; the grid import/export profile (Figure 8) reflects the same anticipatory logic.

Under reactive control (Figure 9), the contrast is structural: mean SoC $\approx 14\%$, BESS at SoC_{min} in 81% of hours, full charge in only 0.2%. The reactive controller depletes the battery in response to present-moment deficits without anticipating future high-value discharge opportunities. Implications for BESS procurement are developed in Section 5.1.

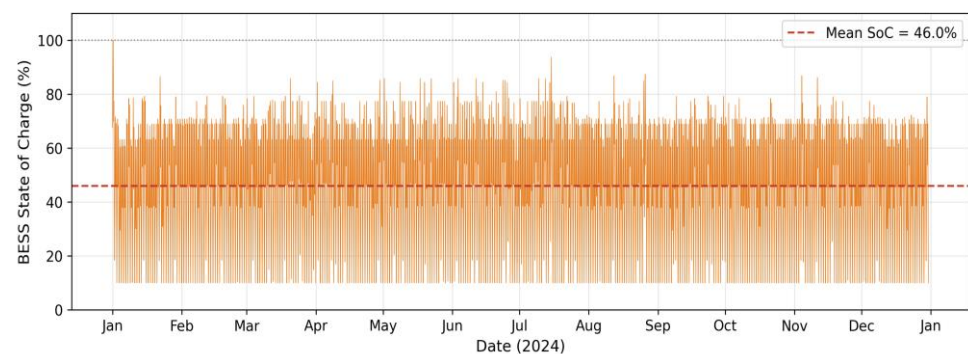


Figure 6. Annual BESS SoC under MPC control.

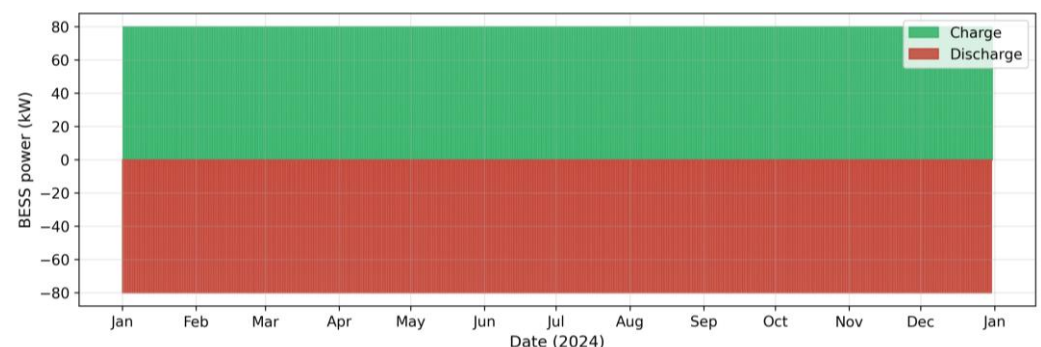


Figure 7. BESS cycling under MPC control: (a) monthly charge and discharge energy throughput across 2024; (b) hourly charge (-)/discharge (+) power with the state-of-charge trace over the most-active representative week (8–14 July), showing the daily arbitrage cycle.

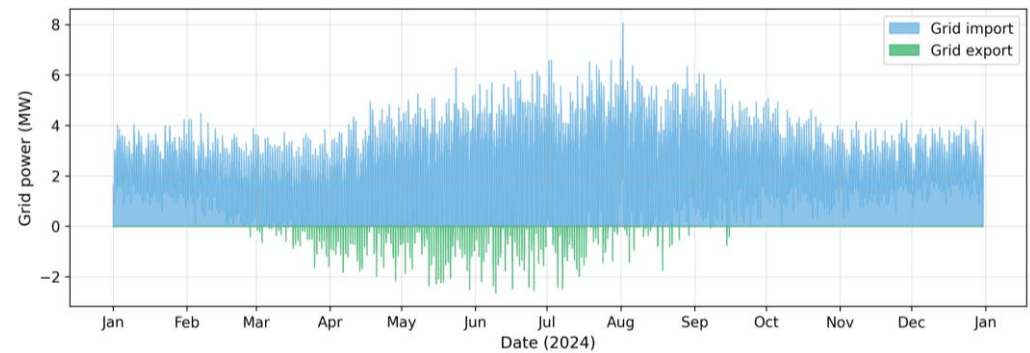


Figure 8. Annual grid import (+)/export (−) under MPC.

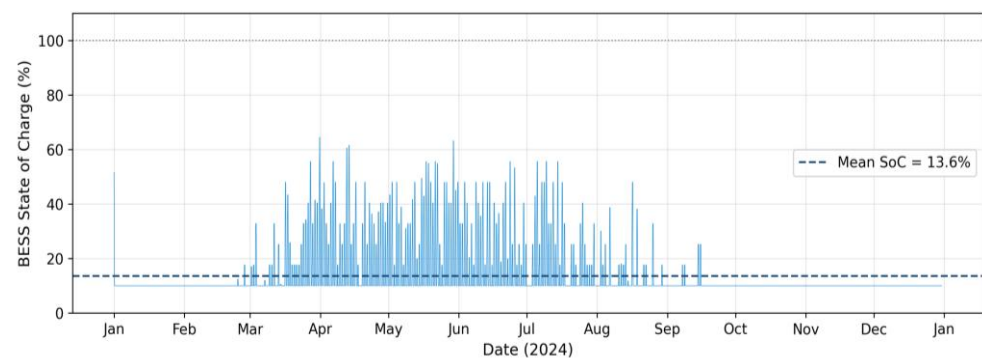


Figure 9. Rule-based EMS: annual BESS SoC under reactive control.

4.3. Annual Comparison and Weekly Detailed Profile

A weekly comparison (Figure 10) shows the MPC delaying discharge until the price signal turns favourable while the RB depletes early; after one week, the MPC's cumulative cost is significantly lower despite higher round-trip losses.

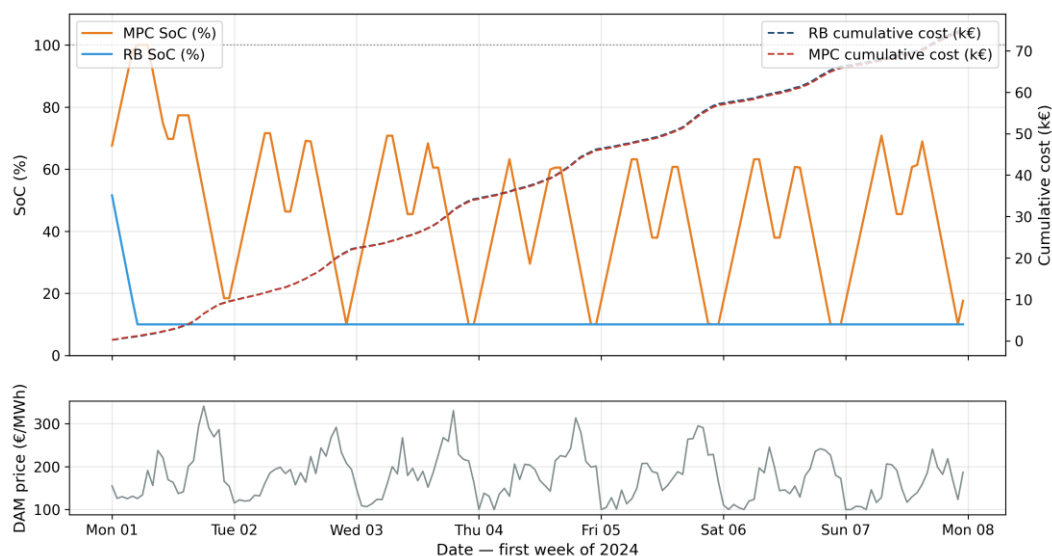


Figure 10. Weekly MPC (orange) vs. RB (blue): SoC and cumulative cost (**top**), realised hourly purchase price (**bottom**). The SoC axis is drawn to 110% with a dotted 100% reference line; the state of charge is hard-bounded at 100% by Equation (4) and never exceeds it.

Annual aggregates for all three controllers are summarised in Table 5. On the identical 1 MWh/±80 kW configuration, the reactive rule-based controller spends €3,316,102; the enhanced RB*, permitted only causal price-threshold grid charging, spends €3,307,291—a

savings of €8811 (0.27%) achieved with no predictive information whatsoever; and the MPC spends €3,301,639, a savings of €14,463 (0.44%) over the reactive baseline. The MPC therefore improves on RB⁺ by €5652 (0.17%): of the €14,463 reactive-baseline gap, roughly 61% is the value of permitting grid charging and 39% the value of predictive optimisation proper. Both effects also restructure the asset—RB⁺ alone already raises the mean SoC from 13.6% to 38.7% and cuts the minimum SoC residence from 81% to 18%—but the MPC pushes this the furthest (46.0%; 6%), so anticipatory control delivers the largest structural shift together with a measurable, if modest, additional economic gain at the pilot scale.

Table 5. Annual performance on the identical 1 MWh/±80 kW configuration (2024): reactive rule-based, enhanced rule-based with causal price-threshold grid charging (RB⁺), and MPC. The three-way layout isolates the value of grid-charging permission (reactive → RB⁺) from the value of predictive optimisation (RB⁺ → MPC).

Metric	Rule-Based (Reactive)	RB ⁺ (Grid Charging)	MPC
Total annual energy cost (€)	3,316,102	3,307,291	3,301,639
Savings vs. reactive baseline (€)	—	8811 (0.27%)	14,463 (0.44%)
Residual MPC value vs. RB ⁺ (€)	—	—	5652 (0.17%)
Mean BESS state of charge	13.6%	38.7%	46.0%
Hours at SoC_{min} (% of year)	81%	18%	6%
Hours at SoC_{max} (% of year)	0.0%	0.0%	0.0%
Annual grid export (MWh)	338.4	340.7	364.1
Annual grid import (MWh)	21,288	21,307	21,341
Annual net grid energy (MWh) ¹	20,950	20,966	20,977
Annual CO ₂ emissions (t CO ₂ eq, Italian grid)	4734.7	4738.4	4740.9

¹ Net grid energy = import – export. The +27 MWh reactive-to-MPC delta reflects the MPC's higher cycling rate; the controller-level CO₂ figures follow directly at 0.226 kg CO₂eq/kWh.

Table 6 reports the C-rate sensitivity. Raising the power rating from the relay-constrained 0.08 C to 0.5 C roughly doubles the savings (0.44% → 0.93%; €14,463 → €30,897); a further increase to 1.0 C yields no additional gain (0.92%), because at and beyond 0.5 C, the 1 MWh energy capacity, rather than the power rating, becomes the binding constraint. The pilot's modest savings is thus in large part an artefact of the protection-relay power limit, and a 0.5 C retrofit is expected to approximately double it; the shadow-price analysis of Section 5.4 confirms that the energy capacity becomes binding only once the C-rate is lifted.

Two distinct carbon effects must be kept separate. At the controller level, the MPC's extra cycling raises the net grid energy by +27 MWh and operational (Scope-2) emissions by +6.2 t CO₂eq (+0.13%) at the 2024 Italian average grid factor of 0.226 kg CO₂eq/kWh—a small increase, stated plainly, that is specific to the 1 MWh pilot and reverses at larger capacity (BESS embedded emissions of 50–100 kg CO₂eq/kWh LFP amortise to 5–10 t/yr over 10 y [66]; the marginal CCGT factor is 0.4–0.5 kg CO₂eq/kWh). At the system level, and entirely independently of the controller, electrifying the berths displaces at-berth fuel combustion: the AFIR-systemic gain is [7.5, 13] kt CO₂eq/yr at the 19.97 GWh cold-ironing supply (60–80% connection rate, EMEP/EEA 2023 0.69–0.85 kg CO₂eq/kWh auxiliary factor, 5–8% shore-side loss)—three orders of magnitude larger than the controller-level + 6.2 t, and a benefit that accrues regardless of whether the BESS is dispatched by MPC or by either rule-based controller.

Initial-condition and warm-up sensitivity. Discarding {24, 168, 336, 720} h yields €14,387/€14,048/€13,655/€12,688, with the qualitative ordering preserved. Block-length L

$\in \{24, 72, 168, 336\}$ h yields 95% percentile CIs [€13,586, €15,331], [€13,314, €15,478], [€12,863, €15,771] and [€12,161, €16,186]; the realised savings lies within all four.

The moving-block bootstrap ($L = 168$ h, $B = 10,000$) places a 95% percentile CI of [€12,842, €15,742] (0.387–0.475%); the basic/reverse percentile interval is [€13,184, €16,084]. The CI quantifies within-year re-arrangement variability on the single 2024 trajectory under weekly-block dependence; it is not a credible interval over a population parameter. The block-bootstrap interval is modestly wider than the i.i.d. counterpart on 365 daily blocks ([€13,642, €15,275]), the correct accounting for loss-differential autocorrelation. Implications are developed in Section 5.1, scaling in Section 5.7 and the MILP vs. RL positioning in Section 5.4.

Table 6. C-rate sensitivity: full-year MPC savings over the reactive rule-based baseline as the BESS power rating is raised on the same 1 MWh pack (identical forecasts, data and initial states). Equivalent full cycles (EFCs) are annual throughput $\div 2 \div$ capacity.

BESS Power (C-Rate)	MPC Savings (€)	Savings (%)	MPC Mean SoC	MPC EFC yr ⁻¹
± 80 kW (0.08 C, deployed pilot)	14,463	0.44	46.0%	305
± 500 kW (0.5 C, target)	30,897	0.93	57.7%	675
± 1000 kW (1.0 C)	30,591	0.92	55.2%	707

4.4. Forecast Accuracy Validation

Table 7 summarises the per-stream error metrics (MAE, RMSE, sMAPE and MASE against lag-1, lag-24 and lag-168 naïve baselines); per Hyndman-Koehler [67], $MASE_{24}$ is the discipline-standard for hourly data with diurnal cycles. The framework attains sub-7% sMAPE on the CI-loaded port demand (the highest-impact stream, $MASE_{24} = 0.44$) and 9–18% sMAPE across the four other streams (Figure 11) ($MASE_{24} = 0.72$ – 0.74 for auxiliary demand and the two price streams). The PV-production forecaster *ties* the seasonal-24 baseline ($MASE_{24} = 1.02$): under realistic weather inputs, a clear-sky-corrected model offers limited improvement over “same hour yesterday”; $MASE_{168} < MASE_{24}$ ($0.94 < 1.02$) reflects the dominance of day-to-day cloud-cover variability over weekly seasonality. The negative bias on CI demand (-2.07 kWh/h; annual -18.2 MWh) and PV is consistent with a slightly conservative forecasting layer, on the safe side under cost minimisation.

Table 7. Forecast accuracy metrics for the five EMS streams (full 8784 h 2024). $MASE_1 = 1$ h persistence; $MASE_{24}$ = same-hour-yesterday (the discipline-standard hourly-diurnal naïve [67]); $MASE_{168}$ = same-hour-last-week. $MASE < 1 \Rightarrow$ forecaster outperforms the baseline.

Stream	N (h)	MAE	RMSE	nMAE	sMAPE	$MASE_1$	$MASE_{24}$	$MASE_{168}$	Bias (Forecast – Actual) ¹
Port demand (with cold ironing)	8784	226.6 kWh	297.8 kWh	6.6%	6.8%	0.67	0.44	0.47	-2.07 kWh/h (annual sum: -18.2 MWh)
Port demand (auxiliary only)	8784	103.2 kWh	138.9 kWh	9.1%	10.3%	0.62	0.72	1.02	$+0.77$ kWh/h (annual sum: $+6.8$ MWh)

PV pro- duction	8784	161.1 kWh	330.0 kWh	15.7%	17.6%	0.49	1.02	0.94	−0.24 kWh/h (an- nual sum: −2.1 MWh) +0.83 €/MWh (an- nual mean offset; sum across 8784 h: +7.26 €/MWh) +0.93 €/MWh (an- nual mean offset; sum across 8784 h: +8.16 €/MWh)
DAM pur- chase price	8784	14.78 €/MWh	20.61 €/MWh	9.7%	9.2%	0.64	0.74	0.79	
DAM sale price	8784	16.30 €/MWh	21.56 €/MWh	13.3%	13.4%	0.64	0.73	0.79	

¹ Bias = per-observation mean forecast – actual; “annual sum” is the total accumulated bias over 8784 hourly observations.

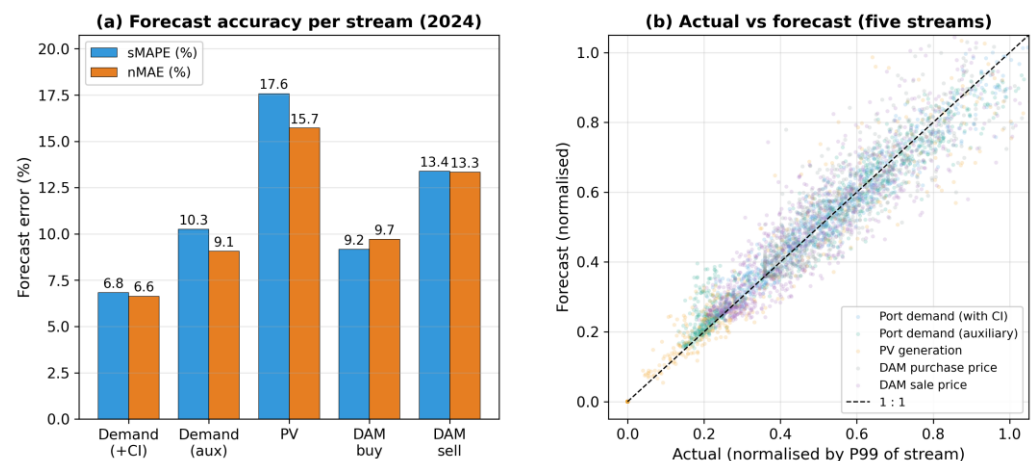


Figure 11. Forecast accuracy validation across the five EMS streams (full-year 2024). (a) sMAPE and nMAE by stream; CI-loaded demand sub-7%, PV the noisiest at ~18%. (b) Actual vs. forecast scatter normalised by 99th percentile, with 1:1 reference.

The accuracy profile passes the literature thresholds: 5–15% sMAPE for European DAM forecasting [49,50] and 10–20% for PV under realistic weather inputs [54,56]. Residual error is the principal source of the gap between the optimal dispatch on forecasts and realised dispatch on actuals. H1 vs. H2 drift (descriptive): four streams stable (drift ≤ 0.32 pp), PV drifts +3.08 pp (16.10 $\rightarrow$ 19.18%) due to autumn–winter cloud-cover variability.

DM test against seasonal-24 naïve. The Histogram Gradient Boosting purchase price forecaster cuts the MSE from 7.76×10^{-4} to 4.24×10^{-4} (€/kWh)² (45.4%). Diebold–Mariano with Newey–West HAC [68,69] at $L = \lfloor N^{1/3} \rfloor = 20$ rejects the null at DM_HAC = −21.68 ($p < 10^{-100}$; effective $N \approx 6444$); i.i.d. variant DM = −25.3; lag grid $L \in \{20, 40, 80, 120, 168\}$ yields DM_HAC $\in \{-21.68, -21.40, -19.90, -18.61, -17.03\}$, with rejection invariant. ADF rejects the unit-root null (−35.28); KPSS rejects level-stationarity at $\alpha = 0.05$ (1.86), so the series is approximately (co)variance-stationary in the sense required for the asymptotic-normal DM-HAC interpretation. Bonferroni across seven implicit tests at family-wise $\alpha = 0.05$ leaves all rejections intact.

5. Discussion

5.1. Anticipatory Versus Reactive Control

The structural contrast in BESS utilisation is the most informative result. Reactive control idles the battery at SoC_{min} for 81% of the year, an expensive idleness that forfeits the asset's principal economic value, whereas anticipatory control cycles the same battery and turns it from passive backup into an active price-arbitrage instrument. The Section 4.3 decomposition makes the source of this shift precise rather than conflated. Permitting the rule-based controller to grid-charge on a causal price threshold (RB⁺) recovers €8811 yr⁻¹ (0.27%) on its own—about 61% of the reactive-baseline gap—and already lifts the mean SoC to 38.7% and cuts the minimum SoC residence to 18%; a substantial part of both the savings and the structural shift therefore follows merely from allowing price-aware charging, not from optimisation. The residual €5652 yr⁻¹ (0.17%) is the value of predictive optimisation proper: foresight buys a further mean SoC lift to 46.0% and a reduction in minimum SoC residence to 6%, concentrated in arbitrage timing (net grid energy differs by <0.25% across all three controllers, so the value is in when energy is moved, not how much). The headline operational finding is unchanged but now honestly bounded: most of the asset-utilisation transformation comes from permitting anticipatory charging, and predictive control realises it most fully while adding a modest but genuine economic increment on top. A port that procures storage without at least price-aware—and ideally predictive—control recovers only a fraction of the asset's economic potential.

Figure 12 reports the monthly cost decomposition and cumulative trajectory: the gap is largest in high-demand/high-volatility months (Jan, Feb, Jul, Aug, and Dec) when CI pulses coincide with price spikes, and narrows but stays positive in shoulder months. The cumulative trajectory is monotonically widening with no phase reversal, so the advantage is distributed across the operating year and is not concentrated in extreme-price events.

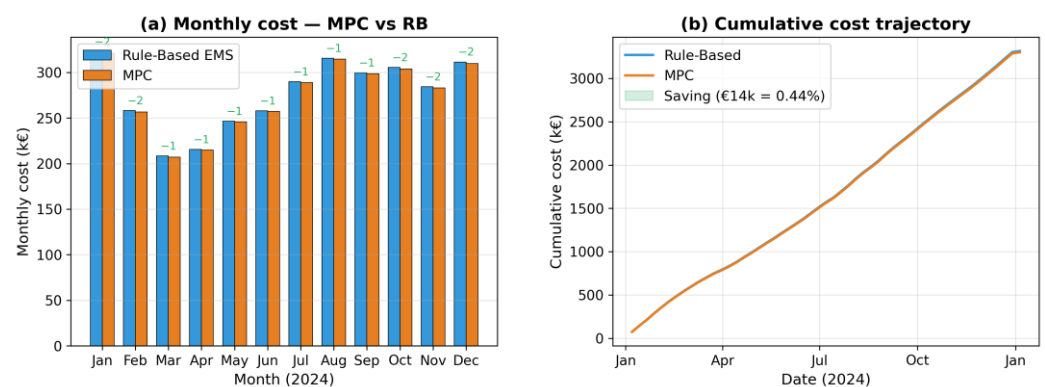


Figure 12. Monthly cost decomposition (a) and cumulative cost trajectory (b) of MPC vs. RB. The gap is largest in winter/summer high-demand months and widens monotonically across the year.

5.2. Battery Operating Regime and the Cycling Cost Question

Figure 13 decomposes the BESS regime. The reactive rule-based SoC distribution is sharply peaked at SoC_{min} (81% of hours) with essentially no high-SoC residence; the MPC distribution is bimodal, with only 6% of the year at SoC_{min} (headroom for forecast PV peaks) and a strong second mode in the 50–60% band. The controllers differ correspondingly in activity: the reactive baseline is actively charging or discharging in only ≈12% of hours (≈6% charging, ≈6% discharging), whereas the MPC is active in ≈89% (≈47% charging, ≈42% discharging)—a 7.5× increase in active-hour frequency and a 7.9× increase in energy throughput.

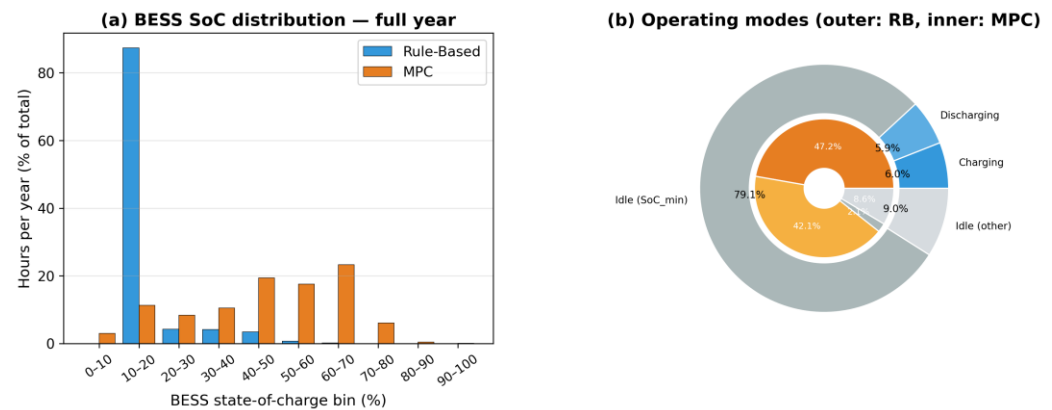


Figure 13. Battery operating regime: SoC distribution and operating-mode utilisation.

This higher throughput is the principal economic caveat, because the MILP objective omits degradation: the Li-ion capacity fade scales with the cumulative throughput and depth of discharge [70,71]. The MPC discharges 289.5 MWh over the year against the reactive baseline's 36.7 MWh—a differential of 252.8 MWh (≈ 267 equivalent full cycles). A simple linear cycling cost penalty applied to this differential erases the entire €14,463 savings at €57.2 per MWh discharged (equivalently $\approx €54$ per equivalent full cycle). Realistic LFP degradation costs bracket this break-even (Table 8): at €250–400/kWh installed and a 4000–6000-cycle life, the implied cost is €46–111 per MWh of throughput, so the net savings spans roughly –€13.6 k to +€2.8 k (mid-case €300/kWh, 6000 cycles $\rightarrow$ +€0.4 k). At the pilot scale, a realistic degradation penalty is therefore of the same order as the gross savings and can consume all of it—which is precisely why the robust result is the structural SoC regime shift rather than the marginal cost figure. The estimate is conservative: it penalises the degradation-blind cost-optimal dispatch, whereas a degradation-aware objective (a rainfall cycle-cost term, L3, Section 5.8) would trade some arbitrage for longevity and recover part of the value. A degradation-aware MILP is consequently the highest-priority model extension.

Table 8. Battery degradation break-even for the 1 MWh pilot. The MPC versus reactive-RB differential discharge throughput is 252.8 MWh yr^{-1} (≈ 267 equivalent full cycles). A linear cycling cost c applied to this differential reduces the €14,463 gross savings to €14,463 – $c \times 252.8$; break-even is $c = €57.2 \text{ MWh}^{-1}$. Implied cost = $\text{CapEx} \times 1000 \div (\text{cycle life} \times 0.9 \text{ MWh usable per cycle})$.

LFP CapEx (€/kWh)	Cycle Life (EFC)	Implied Cost (€/MWh)	Net Savings (€)
250	6000	46.3	+2759
250	4000	69.4	–3093
300	6000	55.6	+418
300	4000	83.3	–6604
400	6000	74.1	–4263
400	4000	111.1	–13,626

5.3. Smart-Port Positioning Within the Smart Cities Literature

The framework instantiates Layer 4 of Yau et al.'s [32] and Bellini et al.'s [30] smart city stacks (Section 3.3), complementary to Bibri-Krogstie [1]. The smart-port is a micro smart city with three particularities: impulse-like CI demand unlike autocorrelated urban-district profiles; AFIR/FuelEU/ETS regulatory drivers with a 2030 timeline absent from residential/commercial deployments; and centralised port authority control making unified EMS deployment tractable where multi-stakeholder urban governance is not.

Three transferable lessons emerge for smart city practitioners outside ports. (i) Structural versus economic decoupling (the SoC regime shift of Section 4.3) is independent of E and generalises to any storage-plus-predictive-control deployment (residential community, electric-bus depot, district-heating storage); absolute savings scales with hardware, so investment cases presenting controller and storage as independent options systematically misprice both. (ii) Forecast accuracy threshold (sub-7% sMAPE on the highest-impact stream, $MASE_{24} \leq 0.74$ on demand/price) is the deployable benchmark; pilots above these margins should expect MPC's advantage to compress. (iii) Data contract defines a portable interface for single-node hubs (port quay, campus, district-heat substation, prosumer aggregator); multi-node networks with line-flow constraints, sector coupling or multi-actor revenue allocation require extensions. Data preconditions: hourly metered demand, DAM/tariff signal with material peak-to-trough spread, BESS sized so daily arbitrageable energy is a non-trivial fraction of daily net consumption. Three port-city interfaces are operationalised. Citizen air quality: at EMEP/EEA 2023 Tier-3 NO_x factors of 8–14 g/kWh for MGO/MDO [63], the 19.97 GWh CI supply at 70% connection rate displaces ≈ 110 –200 t NO_x /yr with comparable PM and SO_x reductions. Neighbouring grid: the port acts as a flexible distribution network aggregator. Regulator audit: the EMS dispatch log provides the evidentiary backbone for AFIR/FuelEU/EU ETS compliance [6–8].

5.4. Operations-Research Framing and Decision-Support Signals

The MILP belongs to the OR tradition of multi-period programming under uncertainty [21,22,41]. The MILP-over-RL choice reflects three priorities for smart-port governance: auditability, shadow-price duals as a by-product, and speed (sub-second 24-step solves). The data interface and Table 2 parameters form a domain-agnostic data contract for cross-border smart-port and energy-cooperative governance [27,72].

Shadow-price results. We extract the constraint duals at every solve by fixing the binary mode variables at their MILP-optimal values and re-solving the resulting linear program. Three findings follow. First, the dual on the power-balance constraint (Equation (2)) tracks the realised hourly purchase price almost exactly—mean $\text{€}151 \text{ MWh}^{-1}$ against a mean purchase price of $\text{€}152 \text{ MWh}^{-1}$, Pearson correlation 0.99—confirming that the extraction recovers the economically correct marginal value of energy at the bus. Second, the dual on the upper SoC bound ($\lambda_{\text{SoC-upper}}$, Equation (4)), the marginal value of an additional kWh of BESS capacity, is non-zero in only 0.03% of hours and averages $\approx 0 \text{ €/kWh}$: at 0.08 C, the battery essentially never reaches full charge, so the binding resource at the pilot is the $\pm 80 \text{ kW}$ power rating, not the 1 MWh energy capacity. Third, the lower-bound dual $\lambda_{\text{SoC-lower}}$ binds in 3.4% of hours, where the controller would discharge below the floor if permitted. Together these duals convert the optimisation into a concrete investment signal: at the deployed configuration, the marginal euro is best spent on power (a higher-C-rate protection scheme), not on energy capacity—exactly as the C-rate sweep of Section 4.3 shows, where the savings doubles at 0.5 C and the capacity becomes binding only thereafter. Systematic year-round extraction of the full dual time series (additional reproducibility-package data) is the natural Real-Time-Offline research artefact.

Multi-actor extension. The MILP treats the port as a single decision-maker; the smart-port literature [2,3,31] recognises a multi-actor ecosystem. Extension requires either a coalitional-game layer (Shapley/nucleolus allocation under shared information) or a Stackelberg/principal agent layer (port authority sets incentives, concessionaires best-respond under asymmetric information). Both preserve the MILP kernel, and the present results correspond to the upper-bound coalition outcome under perfect information.

5.5. Comparison with the Published Port-EMS and Microgrid-MPC Literature

Comparator data are given in Table 9. The 0.44% savings lies at the low end of the microgrid-MPC range (5–15%) [17,18,26] because the BESS C-rate (0.08) is an order of magnitude below the comparator range (0.5–1.0 C); at the 0.5 C target, the savings rises to 0.93% (Table 6), within the published range. Whether 0.44% is practically significant deserves a frank answer: at the 1 MWh pilot, it is not, on its own, a compelling business case (it is a fraction of the BESS amortisation, Section 5.7), and a port operator would not deploy MPC for the energy-cost savings alone at this scale. Its value at the pilot is as a structural demonstration and as the control layer that becomes economically decisive once the BESS is sized and rated for arbitrage (Section 5.7) and once the flexibility and ancillary-service revenues are stacked on top (Section 5.8). This study is, moreover, alone in providing a named-port empirical evaluation against real DAM prices over a complete operating year. The vessel database CI architecture addresses the impulse-like demand structure absent from commercial/industrial comparators. RL approaches are sophisticated but operationally immature (simplified simulation environments, no named-port multi-year validation, seconds-to-minutes per inference plus a training-time premium [23]); adjacent smart-monitoring work [73] has not been transposed to port-energy dispatch.

Table 9. Comparison against published microgrid-MPC/port-energy studies (controlled-comparison and annual/full-year results only). Heterogeneous metrics across system scales, BESS sizes and market regimes, so the comparison is directional rather than strictly normalised.

Study	System	BESS	Savings over Base-line	Headline Forecast Metric
Sachs & Sawodny 2016 [17]	Diesel-PV-battery rural microgrid	100 kWh	8–14% vs. heuristic	n/a
Parasio et al. 2014 [26]	Stylised microgrid	not stated	11% vs. MILP-no-MPC	n/a
Sigalo et al. 2021 [18]	UK grid-connected microgrid	200 kWh	7.5% vs. heuristic	n/a
Tostado-Véliz et al. 2022 [44]	Isolated H2-storage microgrid	100 kWh	12% vs. deterministic-MPC	n/a
Lago et al. 2021 [50]	European DAM forecasting	n/a	n/a	sMAPE 4.6–9.8% (best)
Present work	Port of Ancona, full-year 2024	1.0 MWh/±80 kW (0.08 C)	0.44% vs. rule-based (95% CI 0.39–0.48%); 0.93% at 0.5 C	sMAPE 6.8% (port demand), 9.2% (DAM buy)

5.6. Implications for the Adriatic–Ionian Region

The Adriatic–Ionian basin contains ≈200 commercial/fishing ports [74], with a few tens of these in the AFIR/FueEU TEN-T subset [6,75]. Regulatory phase-in is asymmetric: Ancona (TEN-T core) sits in the first 2030 cohort; Split (TEN-T comprehensive) faces a later phase-in; AD Marina Bar (non-EU candidate) tracks AFIR through regional cooperation rather than direct obligation. Parameterisation absorbs this heterogeneity: full five-stream MPC for ports with AIS/smart-metering/DAM access, simplified BESS-only configuration for smaller ports under the Section 5.3 preconditions. The MILP, solver code and output schema remain invariant, providing software-defined portability [32,58].

Three observations bear on the comparative reading. First, the relative MPC savings sits at the low end of the comparator range, mainly because the BESS C-rate (0.08, Section 3.4) is low relative to the comparator studies (typically 0.5–1.0 C). Second, this study alone provides a named-port empirical validation; the comparator studies use stylised configurations or unspecified contexts. Third, the forecast accuracy lands within the published acceptance range for European DAM forecasting and extends the validation to four additional streams (PV production, sale price, port demand with CI, port demand without CI) that comparator DAM studies do not jointly evaluate.

5.7. BESS-Size Scaling and the Structural Versus Economic Distinction

The structural finding (anticipatory control unlocks the storage asset's full operating envelope, Section 4.3) is independent of E . The economic magnitude (€14,463/yr) is bounded by the 1 MWh/±80 kW pilot configuration. With a 100 €/MWh peak-to-trough on high-volatility days (larger than the Section 3.1.3 P10–P90 of order €60/MWh) and round-trip efficiency of 0.9025, the per-cycle bound is $(1 \text{ MWh} \times 100 \text{ €} \times 0.9025) \approx \text{€90}$; across 8760 h and 1–2 effective daily cycles, this matches the realised savings.

Rather than extrapolate, we simulated the 20 MWh/±10 MW target-state configuration directly. Re-running the identical MPC and reactive rule-based controllers at 20 MWh/±10 MW (0.5 C) over the same 2024 year yields a gross arbitrage savings of €567,703/yr (17.2%)—substantially larger than the ≈€290 k/yr a naive linear extrapolation of the pilot would suggest [15,16,18], because the pilot is power-starved (0.08 C) and relieving the power constraint unlocks disproportionately more value. The 20 MWh MPC raises annual export from 364 MWh to 5940 MWh and cycles ≈ 620 equivalent full cycles, confirming that at this scale, the asset operates as a genuine arbitrage resource rather than a buffer; daily arbitrageable energy (≈40 MWh) now approaches ≈70% of daily net-grid energy (≈57 MWh from Table 5), so the price-taker assumption is itself near its limit.

This gross figure must be bounded by degradation. At ≈11,700 MWh of annual discharge throughput, the linear cycling cost penalties of Section 5.2 (€46–111 per MWh) imply €0.5–1.3 M/yr of degradation cost—of the same order as, and potentially exceeding, the gross savings—so the net value at 20 MWh depends critically on a degradation-aware objective and on the achievable price spread. A degradation-aware controller would cycle less and capture a smaller but durable margin, plausibly back within the €150–250 k/yr range that a concavity-corrected extrapolation indicated. Against an amortised CapEx of €0.6–1 M/yr (€250–400/kWh installed [15,16], 10 y life, 5% discount), arbitrage alone does not close the business case at 20 MWh; the decisive economics require stacking the revenue streams excluded from the present objective—energy-flexibility and ancillary-service payments and energy-community incentives [76]—onto the arbitrage margin (Section 5.8). The pilot itself (€14,463/yr against €32–52 k/yr amortised CapEx) is therefore methodological validation, not an arbitrage-self-sufficient deployment.

5.8. Limitations

(L1) Synthetic/approximate demand inputs. The CI demand is a post-AFIR projection (19.97 GWh) from vessel database assumptions rather than metered berth consumption; operational validation is reserved for future work. (L2) Single-objective formulation. Cost minimisation drives several environmental indicators but does not prioritise emissions when in conflict; under direct carbon pricing, the objectives align; otherwise, a weighted carbon penalty is needed. (L3) No BESS degradation modelling. The MPC's higher cycling rate accelerates capacity fade; section 5.2 shows that a realistic linear cycling cost (€46–111 per MWh of throughput) is of the same order as the gross savings and can erase it, so a rainflow cycle-depth penalty [15]—converting the MILP to a piecewise-linear or MINLP form—is the highest-priority model extension. (L4) Deterministic forecasts. The MILP treats forecasts as point

estimates; stochastic/robust MPC extensions [19] would chance-constrain it. (L5) MCP training spans the 2021–2022 crisis. A rolling-window retraining (24–36-month memory) would eliminate the pre-crisis distributional mismatch. (L6) Weighted-sum convexity caveat. The current MILP is convex (linear objective, binary only through mode selection); multi-objective extensions should re-verify convexity before weighted-sum aggregation. Additional caveats. (a) Hard SoC/grid bounds: real-time deployment may need slack-variable soft constraints [45]. (b) Single-year empirical scope: cross-year (2023 prices) and follower-port (Split, AD Marina Bar) robustness require additional EMS runs (future work). (c) 75% cold-start CI assumption: a ± 10 pp propagation would shift annual CI by ± 1.3 GWh, and future metered shore-power will close this loop. (L7) Single-revenue objective. The objective captures only wholesale energy arbitrage; energy-flexibility and ancillary-service market participation and energy-community incentives [76] are excluded, yet at the larger 20 MWh scale, these stacked revenues are likely necessary to close the business case (Section 5.7) and constitute the principal economic extension.

6. Conclusions

A rolling-horizon MILP-MPC EMS for smart-port decarbonisation has been evaluated over a full 2024 year of realised Italian Day-Ahead Market prices, against a deterministic rule-based controller on an identical configuration—with the dominant cold-ironing load supplied as a post-AFIR projection. The framework instantiates Layer 4 of Yau et al.'s [32] and Bellini et al.'s [30] smart city stacks (complementary to Bibri-Krogstie [1] and Gonzalez-Gil et al. [77]), adopts an MILP kernel that delivers globally optimal dispatch with shadow-price duals and a fully traceable decision log at every solve, and is implemented in open-source Python (PuLP/HiGHS) [59].

The Port of Ancona proof-of-concept (8760 h, 2024 Italian DAM, 6.5 MWp PV, 1.0 MWh BESS) reduces the annual procurement cost by 0.44% (€14,463), raises the mean SoC from 13.6% to 46.0%, increases PV export from 338 to 364 MWh, and cuts SoC_{min} residence from 81% to 6%. The structural lesson is that a port-deployed BESS's principal economic value is unlocked by the control strategy and not by the hardware alone; procurement without a predictive control layer recovers only a fraction of the asset's potential. A controlled decomposition shows that of the €14,463 reactive-baseline gap, $\approx 61\%$ is the value of permitting grid charging and $\approx 39\%$ the value of predictive optimisation proper (€5652 yr^{-1}); the MPC's own operational CO_2 rises by only +6.2 t (+0.13%), a controller-level effect three orders of magnitude smaller than the system-level cold-ironing decarbonisation it enables.

Four contributions follow. (i) MILP-MPC is computationally tractable at port scale (sub-second per 24-step solve). (ii) The 0.44% savings is a conservative small-pilot anchor set by the 0.08 C power limit: the structural finding is independent of E ; raising the C-rate to the 0.5 C target doubles the savings to 0.93%, and a direct 20 MWh/ ± 10 MW simulation yields a €0.57 M yr^{-1} gross arbitrage savings whose net value is degradation-bounded and contingent on stacking flexibility revenues; the investment case is reinforced by AFIR/FuelEU/ETS. (iii) The LP-duality apparatus provides a portable diagnostic toolkit for capacity-investment decisions. (iv) The data contract supports cross-border cooperation in multi-actor smart-port and energy-cooperative settings [27,72,75]. Future extensions include a live forecast feed, a multi-objective MILP with carbon-penalty term [66], degradation-aware dispatch via rainflow counting, follower-port deployment (Split, AD Marina Bar), stochastic/robust MPC [78,79], and progression from Simulator to Real-Time-Online.

Practitioner Implications

(i) Pair predictive control with storage procurement; the BESS-utilisation lift requires the controller. (ii) Calibrate forecasting: sub-7% sMAPE on the highest-impact demand

stream and $MASE_{24} \leq 0.74$ on demand and price streams are the deployable thresholds. (iii) Size and rate the BESS for the price spread regime: at 0.08 C, the 1 MWh pilot caps the savings at ~€14 k/yr, 0.5 C roughly doubles it, and a simulated 20 MWh/±10 MW system reaches €0.57 M/yr gross (degradation- and revenue-bounded net). (iv) Adopt the data contract for single-node hubs; multi-node, sector-coupled or multi-actor settings need extensions. (v) Plan the multi-objective grid-carbon extension to internalise the +0.13% shore-side carbon increase at the small-pilot scale.

Author Contributions: Conceptualization, N.S. and A.K.; methodology, A.K., S.T. and N.S.; software, A.K. and S.T.; validation, A.K., D.C. and N.S.; formal analysis, A.K., S.T. and N.S.; investigation, A.K., S.T. and D.C.; resources, G.A. and N.S.; data curation, A.K. and S.T.; writing—original draft preparation, A.K., S.T. and N.S.; writing—review and editing, N.S., D.C. and G.A.; visualization, A.K. and N.S.; supervision, N.S. and G.A.; project administration, N.S.; funding acquisition, G.A. and N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was carried out within the European Union via Interreg IPA ADRION; project AIMPRESS (Adriatic-Ionian Maritime oPeRational Efficiency and Sustainable Scheme), Grant Agreement No. IPA ADRION 527, co-funded by the European Union.

Data Availability Statement: The data generated and analysed during this study are available from the corresponding author upon reasonable request. In addition, the datasets and methodological outputs may be made publicly available through the AIMPRESS project website and its associated public deliverables.

Acknowledgments: The authors acknowledge the support of the AIMPRESS project, funded under the Interreg ADRION Programme, for providing the operational data, methodological framework, and project infrastructure that enabled this research. The authors also thank the project partners and port authorities involved in the AIMPRESS pilots for their collaboration and for granting access to vessel traffic and energy demand datasets used in the analysis.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

AFIR: Alternative Fuels Infrastructure Regulation; AIS: Automatic Identification System; BESS: Battery Energy Storage System; CI: Cold Ironing; DAM: Day-Ahead Market; EMS: Energy Management System; ETS: Emissions Trading System; MILP: Mixed-Integer Linear Program; MPC: Model Predictive Control; nZEP: nearly Zero Energy Port; PV: Photovoltaic; SoC: State of Charge; TEN-T: Trans-European Transport Network.

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