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Hybrid Renewable Port Microgrids for Cost-Effective Cold Ironing in Small and Medium-Sized Ports

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Abstract

Supplying shore-side electricity to ships at berth, a practice known as cold ironing, removes the emissions of their auxiliary engines, yet the resulting electricity demand is large, highly seasonal and hard to serve economically from the grid at the small and medium-sized ports that make up most of the European network. This study asks how to meet that demand affordably and cleanly. It develops a smart-sizing and energy-management framework for a grid-connected hybrid renewable energy system that jointly optimizes solar photovoltaic and wind capacity together with a combined battery-and-hydrogen storage envelope. An energy-conserving stochastic reconstruction of the hourly cold-ironing demand is embedded within a genetic algorithm that minimizes the levelized cost of energy and the carbon footprint, and the system is operated by a transparent, priority-based controller. On a full year of real operational data from a Mediterranean port, the optimizer selects 380 kilowatts of photovoltaic capacity and a 2064 kilowatt-hour, battery-dominated storage envelope, reaching a renewable penetration equal to 76 percent of annual demand, with 57 percent of demand met without the grid. Relative to grid-only cold ironing it lowers the levelized cost of energy by about 10 percent on a screening basis, before life-cycle costs bring it to roughly grid parity, while cutting greenhouse-gas emissions by 45 percent; emissions fall 72 percent relative to auxiliary engines. Storage capacity, not oversized renewable generation, proves decisive for deep decarbonization, and battery storage dominates the cost-optimal design for this diurnal load. The framework gives port operators a transferable, data-driven decision-support tool.

Keywords: cold ironing; shore-to-ship power; hybrid renewable energy system; genetic algorithm optimization; energy management system; battery-hydrogen storage; port decarbonization



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1. Introduction

Maritime transport is responsible for approximately 2.9% of global anthropogenic greenhouse-gas (GHG) emissions, with a substantial fraction concentrated in port areas where vessels operate auxiliary diesel generators during berthing [1]. The International Maritime Organization (IMO) has set ambitious decarbonization targets, including a 40% reduction in carbon intensity by 2030 and net-zero emissions by or around 2050 [2]. Concurrently, the European Union's Fit for 55 package and the Alternative Fuels Infrastructure Regulation (AFIR) mandate the deployment of shore-side electricity supply at major Trans-European Transport Network (TEN-T) ports by 2030 [3–5]. These regulatory drivers have positioned cold ironing (CI), the practice of supplying shore-side electrical power to a vessel

at berth so that its auxiliary engines can be shut down, as a cornerstone technology for port decarbonization [6,7].

Despite its clear environmental benefits, CI introduces formidable technical and infrastructural challenges. Large commercial vessels at berth can demand between 1 and 12 MW of electrical power, with cruise ships and container vessels at the upper end of this range [6,8]. When multiple vessels are serviced simultaneously, the aggregate CI load can exceed the existing capacity of the local distribution grid, necessitating costly network reinforcements. Moreover, the stochastic nature of vessel arrivals, berthing durations, and onboard energy consumption creates a highly variable demand profile that is fundamentally different from the predictable baseload of terrestrial port facilities [7,9]. For small and medium-sized ports (SMSPs), particularly those within the TEN-T, these challenges are amplified by limited grid infrastructure, constrained spatial footprints, and tighter financial margins compared to large hub ports [10,11].

The conventional approach of powering CI exclusively from the terrestrial grid carries two critical drawbacks. First, in regions where the grid carbon intensity remains high, as is the case in several Mediterranean countries where fossil fuels still dominate the electricity mix, the net emission reduction from CI is substantially diluted [12,13]. Second, the incremental CI demand can trigger grid upgrade costs that render the business case for CI uneconomical for SMSP operators [14–17]. These limitations motivate the integration of local renewable energy sources to supply a meaningful share of the CI load directly, thereby reducing both grid dependency and the effective carbon footprint of shore-power operations [18,19].

Hybrid renewable energy systems (HRES) that combine photovoltaic (PV) and wind generation offer a promising pathway. PV and wind resources exhibit complementary temporal profiles in Mediterranean coastal environments: PV generation peaks during summer midday hours, coinciding with high cruise-season CI demand, while wind resources are often stronger during winter months when port facilities draw higher baseline loads [20,21]. When coupled with battery energy storage and hydrogen storage subsystems, an HRES can buffer the intermittency of individual renewable sources and provide dispatchable power for CI operations [22,23]. However, the design of such a system involves a complex, multi-dimensional optimization problem. The capacities of PV, wind, and storage components must be sized not only to meet the CI demand at acceptable reliability but also to minimize the levelized cost of energy (LCOE) and the life-cycle carbon footprint, all while respecting the physical constraints of the port environment and the operational characteristics of the local grid [24,25].

The port energy transition is further shaped by the emergence of hydrogen as a versatile energy carrier for industrial port areas [26] and by the growing policy momentum behind shipping decarbonization [27–29]. For SMSPs, the deployment of renewable-powered CI represents not merely an emissions compliance exercise but a strategic opportunity to reduce operational energy costs, enhance energy autonomy, and position the port as a sustainability leader within its regional maritime network into a cooperative approach [30].

This study addresses the identified gap by proposing an integrated smart sizing and energy management framework for grid-connected HRES supporting CI in SMSPs. The framework comprises four interconnected components: (i) an enhanced, energy-conserving stochastic cold ironing demand model, Port-Conditioned, Constraint-Aware, Energy-Conserving Stochastic Disaggregation (PC-ECSD), that reconstructs a physically consistent hourly at-berth load profile from sparse call-level records by coupling the vessel load to the observed port operational state; (ii) physically based photovoltaic and wind generation models driven by on-site resource data; (iii) a genetic algorithm (GA)-based optimization engine that jointly sizes the renewable capacities and the battery–hydrogen

storage envelope to minimize LCOE and GHG emissions; and (iv) a transparent rule-based Energy Management System (EMS) that coordinates renewable generation, battery storage, hydrogen storage, and grid exchange to ensure reliable coverage of the CI load under stochastic conditions. The methodology is demonstrated on a representative Mediterranean SMSP using a full year of hourly operational data.

The novelty of this work lies not in any single component, since genetic algorithm sizing, rule-based energy management, battery–hydrogen storage, and cold ironing are all individually established, but in their integration around the atypical, peaky structure of cold-ironing demand. The principal contributions are methodological: (a) an enhanced, transferable cold ironing demand model, termed Port-Conditioned, Constraint-Aware, Energy-Conserving Stochastic Disaggregation (PC-ECSD), that reconstructs a physically consistent, strictly energy-conserving hourly at-berth load profile from sparse call-level records, coupling the vessel load to the observed port operational state and propagating timestamp and stay-duration uncertainty; (b) the embedding of this cold-ironing-specific demand model directly inside the genetic algorithm fitness evaluation, so that every candidate configuration is sized against the actual hourly cold ironing load rather than an annual-energy proxy, with the storage autonomy treated as a swept design variable rather than fixed a priori; (c) a power-energy-matched hybrid battery–hydrogen storage formulation, coordinated by a transparent rule-based Energy Management System (EMS), in which the battery-to-hydrogen split is itself an optimization variable, so that the framework identifies the economically preferred storage technology for a given load rather than presupposing a mix; and (d) a validation of the resulting design against the exhaustively enumerated global optimum and an independent particle-swarm-optimizer benchmark, establishing that the reported configuration is effectively optimal for the problem solved. A compact, adjustable set of sustainability indices spanning economic, environmental, social, technological and political dimensions is additionally provided as a heuristic multi-criteria decision aid (Section 3.7). The empirical findings obtained with this framework, namely that the cost-optimal renewable mix follows the demand seasonality and that storage sizing rather than renewable oversizing is the decisive lever for deep decarbonization, are outcomes of the study and are reported as results in Sections 4 and 5.

The remainder of this paper is organized as follows. Section 2 reviews the state of the art in cold ironing, port energy systems, HRES optimization, and energy management. Section 3 details the materials and methods, including the case study port, the energy modeling framework, the GA optimization formulation, and the EMS architecture. Section 4 presents the optimization results, the optimal system configuration, and the comparative performance against baseline scenarios. Section 5 discusses the implications, limitations, and scalability of the proposed framework. Section 6 concludes with policy recommendations and directions for future research.

2. State of the Art

2.1. Cold Ironing Technology and Deployment

Cold ironing, also called shore-to-ship power or alternative maritime power, lets a berthed vessel connect to the terrestrial grid and switch off its auxiliary diesel generators. It has been deployed at a growing number of ports, from early adopters such as Los Angeles and Gothenburg to several European cruise terminals, typically through a shore-side substation delivering 6.6 or 11 kV at 50 or 60 Hz [6,10]. Its environmental value is well established but conditional: switching from auxiliary engines to grid power cuts individual at-berth pollutants (carbon dioxide, sulfur oxides, nitrogen oxides, particulate matter) by 30 to 95 percent, yet the net greenhouse-gas benefit depends entirely on the grid mix,

ranging from near-complete decarbonization on a renewable grid to a mere displacement of local air pollution to the power plant on a fossil-dominated one [11–13].

The picture is sharper for small and medium-sized ports. These serve fewer and smaller vessels, ferries, short-sea cargo, and occasional cruise calls, so their cold-ironing load is lower but far more intermittent, and the infrastructure must be amortized over fewer annual events, leaving the business case marginal [12,14,22]. Systematic and bibliometric reviews identify economic viability, grid-capacity limits, and institutional coordination as the dominant barriers for this segment, which remains understudied relative to large hub ports [23,24]. Structured methods for estimating cold-ironing demand from vessel-traffic and berth-occupancy data [25] provide the template for the demand-characterization step used here.

2.2. Renewable Energy Integration in Ports

The green-port or nearly zero-energy-port concept envisions port operations supplied predominantly by locally generated renewables [9,18,19]. Rooftop and land photovoltaics are the most immediately deployable option, owing to their modularity and low operating complexity, whereas wind offers higher capacity factors at coastal sites but faces navigational-safety, radar, and visual-impact constraints [9,19,31]. In Mediterranean settings the two resources are temporally complementary: photovoltaic output peaks in summer, coinciding with cruise-season cold-ironing demand, while wind is stronger in winter.

Techno-economic studies consistently show that high renewable penetration for port and coastal loads is achievable only when adequate storage bridges the temporal mismatch between generation and demand; hybrid photovoltaic–wind–hydrogen and wind–wave-storage systems both reach high renewable fractions but hinge on storage sizing [20,21]. Hydrogen is increasingly cast as an enabler of port-area decarbonization and of longer-duration buffering across multi-day vessel-free intervals [26], while policy analyses note that the shore-power mandate creates a regulatory pull rewarding systems-level planning over a compliance-minimizing, grid-only approach [27].

2.3. Optimization Approaches for HRES Sizing

Optimal sizing of hybrid renewable energy systems is a mature problem [32,33]. Enumeration-based tools such as HOMER rank a discrete set of configurations by net present cost and are accessible to practitioners, but they scale poorly to continuous, multi-objective design spaces [33]. Metaheuristics, chiefly genetic algorithms and particle swarm optimization, have therefore become the predominant approach, because they handle non-convex, multi-modal landscapes without gradients, accommodate multi-objective formulations, and absorb problem-specific constraints through penalties [34–37].

Reported applications span household and community photovoltaic–wind–battery systems, remote photovoltaic–wind–diesel hybrids and renewable-hydrogen supply. Two findings recur: that Pareto-based multi-objective formulations expose the cost–reliability trade-off hidden by single-objective scalarization [38–43], and that jointly optimizing component capacities together with the dispatch strategy, rather than fixing dispatch a priori, materially lowers net present cost [44]. Hybrid-storage architectures pairing batteries with supercapacitors or hydrogen improve reliability and reduce battery degradation, provided the lower marginal cost of hydrogen-storage capacity offsets the round-trip losses of the electrolyzer–fuel-cell path [45–48]; component-level economic optimization of residential battery storage [49], broad reviews of grid-connected battery systems [50] and of renewable-and-storage technologies more generally [51], and analyses of green versus blue hydrogen for longer-duration options [52] reach compatible conclusions. A recurring quantitative finding is that storage-duration requirements grow nonlinearly once the renewable fraction

exceeds roughly 50 to 60 percent [53], directly relevant to the deep-decarbonization regime targeted here. Process-systems studies, several in this journal, extend the same logic to industrial energy supply through process-and-supply co-optimization, storage co-design, and explicit treatment of stochastic renewable variability [54–58].

A specific gap remains. Genetic algorithm sizing has recently been applied to aggregate cold-ironing loads [4], and nearly zero-energy-port planning and hydrogen-based shore-power concepts have been outlined [5,59]; what has not been addressed is sizing against a physically reconstructed, strictly energy-conserving hourly cold-ironing profile rather than an aggregate or annual-energy proxy. This matters because cold-ironing demand, unlike residential or municipal demand, combines extreme peak-to-average ratios with multi-day zero-demand intervals and strong tourism-driven seasonality, so a system sized for a conventional load of equal annual energy would be undersized for the peak and oversized during the long idle periods. The present study closes this gap by embedding the cold-ironing-specific demand model inside the genetic algorithm fitness evaluation, so that every candidate configuration is stress-tested against the actual hourly load, and by validating the resulting design against the exhaustively enumerated global optimum.

2.4. Energy Management Strategies for Grid-Connected HRES

The Energy Management System decides, at each step, how renewable generation, storage, and grid supply meet the load, balancing renewable self-consumption, grid-import cost, storage limits, and export caps [60,61]. Rule-based strategies that follow a fixed priority order (renewables, battery, hydrogen, grid) dominate practice because of their transparency, low computational cost, and ease of implementation in industrial controllers [62,63]; model-predictive and reinforcement-learning controllers can improve economic performance under time-varying tariffs but add complexity and data requirements that are often unwarranted in small-port settings [64,65].

Comparative studies of metaheuristics for hybrid-system sizing report mixed rankings: genetic algorithms achieve the lowest cost of energy in some photovoltaic–wind–diesel–battery cases [64], while hybrid genetic-algorithm–local-search schemes lead in others with more than three or four decision variables [60,66], confirming that no single algorithm dominates and that benchmarking on the specific problem is warranted. Across these studies the dispatch logic, and in particular the battery-versus-hydrogen priority, exerts a first-order effect on the leveled cost [67–70], with empirical small-scale electrolyzer and fuel cell efficiency data informing the hydrogen-path assumptions [71]. Foundational microgrid reviews frame the surrounding challenges of protection, islanding, and multi-source coordination that carry over to port and shipboard microgrids [72–75].

Several recent process-systems studies advance the same agenda, from multi-storage architectures for coastal loads [76] and deep-reinforcement-learning dispatch reporting double-digit gains in renewable utilization [77] to comfort-and-cost scheduling [78], rule-based storage scheduling as a validation benchmark [79], real-time model-predictive management [80], and carbon-aware dispatch [81]. Against this backdrop the distinctive feature here is that the storage–technology split is not pre-committed but is itself an optimization variable, and the rule-based controller then dispatches according to the discovered split, charging the battery before the electrolyzer and discharging it before the fuel cell, with the grid settling any residual imbalance [67].

2.5. Hydrogen and Hybrid Storage in Energy Systems

A broad review of hybrid-storage sizing, control, and management identifies storage-technology selection as the most consequential design decision after renewable sizing, governed chiefly by round-trip efficiency and capital cost per kilowatt-hour of storage

capacity [82], precisely the trade-off that the present framework resolves endogenously by optimizing the battery-to-hydrogen split rather than fixing it in advance.

3. Materials and Methods

3.1. Case Study Port and Data Acquisition

The case study focuses on a representative small and medium-sized port (SMSP) located in the Mediterranean region and designated as a Trans-European Transport Network (TEN-T) port. The port serves a mixed traffic of ferry, short-sea cargo, and seasonal cruise vessels, with a vessel-call volume typical of Mediterranean SMSPs. Its terrestrial facilities, cargo-handling equipment, lighting, workshops, and administrative buildings constitute a baseline electrical load of approximately 70.4 MWh per annum, while the at-berth electricity demand of visiting vessels constitutes a cold ironing (CI) load of approximately 587 MWh per annum. The total annual port energy demand is therefore approximately 657 MWh, of which the CI load represents 89%. To preserve commercial confidentiality, all data were anonymized and the port is referred to throughout as the “case-study SMSP” without geographic attribution.

Real hourly operational data spanning a full calendar year were obtained from the port’s energy-monitoring records. The dataset comprises: (i) the hourly electrical demand of the port’s terrestrial facilities (kWh); (ii) the at-berth energy consumption of individual vessels, recorded at the vessel level (kWh per call); (iii) hourly solar irradiance (kW/m^2) and ambient temperature ($^{\circ}\text{C}$); and (iv) hourly wind speed (m/s) and temperature from a coastal measurement station.

The vessel traffic pattern exhibits a pronounced seasonality that is decisive for system sizing. Cold ironing demand is strongly concentrated in the May–October cruise and high-tourism season, with monthly CI energy peaking in July and August at roughly 90 MWh per month, and falling to approximately 14–16 MWh per month in the winter months. The combined port-and-CI load reaches a reconstructed peak of approximately 584 kW during multi-vessel summer berthing events, while the median hourly demand is only about 38 kW, and the cold ironing load falls below 1 kWh for 1772 h of the year (about 20%, of which roughly 1741 are strictly zero) when no vessel is at berth. The resulting hourly load factor is 0.13 and the peak-to-average ratio is 7.8, a profile that differs fundamentally from the comparatively flat baseload of conventional municipal or industrial facilities and that dominates the sizing of every system component.

3.2. Cold Ironing Demand Modeling

A critical methodological step is the transformation of sparse, call-level vessel energy records into a continuous, high-resolution hourly cold ironing demand profile suitable for energy-system simulation. The available operational data record each vessel’s electricity consumption as cumulative call-level totals (kWh per berthing event), without intra-call temporal resolution. Because the sizing of every system component is driven by the *shape* of the hourly load, its peaks, its ramps, and its idle intervals, and not merely by its annual energy, a faithful reconstruction of the sub-call profile is essential. To this end, a dedicated Port-Conditioned, Constraint-Aware, Energy-Conserving Stochastic Disaggregation (PC-ECSD) model is developed. The model is constraint-aware (it respects physically plausible power bounds), port-conditioned (the reconstructed ship load is statistically coupled to the observed port operational state), and strictly energy-conserving (the reconstructed hourly energy of every call sums exactly to the recorded call total).

Energy-conserving disaggregation. For each recorded berthing event i of vessel class c , the model distributes the recorded call energy $E_{i,c}$ over a set of occupancy hours Ω_i by

assigning to each hour t a non-negative latent intensity $q_{i,c,t}$ and normalizing it so that the reconstructed hourly energies sum exactly to the recorded call total (Equation (1)):

$$e_{i,c,t} = E_{i,c} \frac{q_{i,c,t}}{\sum_{\tau \in \Omega_i} q_{i,c,\tau}} \quad (1)$$

By construction the redistribution preserves the call energy to machine precision, so the annual energy of every vessel class is conserved exactly. The aggregate cold ironing profile is obtained by superimposing the reconstructed hourly contributions of all events, with calendar wrap-around indexing so that calls spanning the year boundary are correctly placed.

Stay-duration and event-anchor uncertainty. The occupancy window Ω_i is determined by a stay duration sampled, per vessel class, from a triangular distribution parameterized by minimum, modal, and maximum berthing hours (Table 1), with a multiplicative jitter that captures call-to-call variability. Because the recorded timestamp of a call may correspond to the vessel's arrival, its midpoint, or its departure, the model treats the temporal anchor as a latent variable, drawing the interpretation probabilistically and applying an integer start-hour offset; this propagates the timestamp ambiguity of the source records into the reconstructed profile rather than assuming it away.

Table 1. Vessel-class stay-duration and reconstruction parameters used by the PC-ECSD model (anonymized vessel classes; energy values are the recorded annual cold ironing energy per class).

Vessel Class	Annual CI Energy (kWh)	Min Stay (h)	Mode Stay (h)	Max Stay (h)	Intra-Call σ	AR(1) ρ	Port-Coupling λ
VC-1	40,296	5.0	6.0	7.0	0.13	0.55	0.25
VC-2	24,840	2.0	2.5	3.0	0.14	0.45	0.20
VC-3	90,013	2.0	3.0	4.0	0.16	0.50	0.22
VC-4	36,400	5.0	6.0	8.0	0.12	0.60	0.30
VC-5	68,640	5.0	6.0	8.0	0.12	0.60	0.28
VC-6	298,594	1.0	2.0	3.0	0.18	0.35	0.18
VC-7	14,625	1.0	2.0	3.0	0.17	0.35	0.18
VC-8	13,725	1.0	2.0	3.0	0.17	0.35	0.18

Intensity model. The latent intensity q is assembled from four multiplicative factors. (i) A phase profile shapes the within-call load, applying a reduced draw during the ramp-up and ramp-down hours of the berthing event relative to the service plateau. (ii) A latent operational-state multiplier introduces class-specific high-load service states (e.g., elevated auxiliary or reefer loads). (iii) An autocorrelated stochastic term, a first-order autoregressive, log-normally distributed noise process, reproduces realistic hour-to-hour variability while preventing implausible discontinuities. (iv) A port-conditioning factor couples the ship load to the port's own operational rhythm: a standardized weekly baseline anomaly signal of the observed port load, $z(t)$, modulates the ship intensity through $1 + \lambda_c z(t)$, while a diurnal shape factor raised to a class-specific exponent aligns the reconstruction with the characteristic daily activity pattern of the port. The coupling strength λ_c governs how strongly vessel demand tracks port activity.

Constraint-aware projection. In the constraint-aware mode adopted for this study, the normalized profile is additionally projected onto a feasible set: class-specific soft power caps, inferred from the observed call-level energy and the minimum plausible stay duration, bound the hourly power, after which the profile is re-normalized to restore exact energy conservation and lightly smoothed to suppress non-physical spikes, with a final re-normalization. This projection removes the artificial single-hour spikes implicit in the raw sparse records while preserving total energy and the realistic temporal structure.

Monte Carlo ensemble and sensitivity. Because the reconstruction is stochastic, the model is executed as a Monte Carlo ensemble (five runs, fixed random seed 42) and the per-hour mean profile is retained as the nominal cold ironing demand; ensemble convergence is tracked through the run-to-run change in the normalized profile shape. This single fixed ensemble-mean profile, not a freshly resampled realization, is the hourly load used in every optimization evaluation, so the sizing is deterministic with respect to the demand input (the propagation of load stochasticity into the sizing is left to future work, Section 5.5). The sensitivity of the reconstruction to the port-coupling strength is examined by re-running the model across a range of coupling values λ . An optional calibration hook allows the stay-duration distributions to be re-estimated directly from Automatic Identification System (AIS) arrival/departure logs where these are available; in the absence of vessel-tracking data the model relies on the class-level operational parameters of Table 1, and its outputs are interpreted as a physically consistent, energy-conserving reconstruction rather than a metered ground truth.

Validation. The reconstructed profile was validated along three axes (Table 2). First, energy conservation is exact: the reconstructed annual energy of every vessel class reproduces the recorded total to within numerical precision. Second, the temporal grid is strictly regular (uniform one-hour steps across the 8760 h year, with no missing or duplicated stamps). Third, the reconstruction materially improves the physical realism of the load relative to the raw sparse records: it spreads demand from a small number of artificially concentrated hours across the realistic berthing windows, lowering the hourly peak-to-average ratio of the cold-ironing load from approximately 15.4 in the raw records to 8.6 in the reconstruction and raising its hourly load factor from 0.065 to 0.116, while preserving the strong day-level correlation between port and ship activity (≈ 0.71). All statistics in this paragraph and in Table 2 are computed for the cold-ironing (ship) load alone and are therefore distinct in scope from the combined port-and-CI load statistics quoted in Sections 3.1 and 4.1 (peak ≈ 584 kW, load factor 0.13, peak-to-average 7.8). The port-coupling sensitivity confirms that these aggregate statistics are robust to the coupling strength, varying by less than ten percent across the examined λ range.

Table 2. Validation of the PC-ECSD v3 reconstruction of the cold-ironing (ship) load against the raw sparse call-level records. The reconstruction conserves annual energy exactly while substantially improving the physical realism of the hourly profile. All statistics are for the cold-ironing load alone.

Metric	Raw Sparse Records	PC-ECSD v3 Reconstruction
Annual CI energy (kWh)	587,132	587,132 (conserved)
Non-zero hourly records	3537	7019
Peak hourly CI demand (kW)	1035	577
Hourly load factor	0.065	0.116
Hourly peak-to-average ratio	15.4	8.6
Daily load factor	0.419	0.361
Port-ship daily correlation	0.726	0.705
95th-percentile hourly ramp (kW)	143.8	66.6

Energy conservation holds to machine precision for every one of the eight vessel classes. The reconstruction was executed as a five-run Monte Carlo ensemble (constraint-aware mode, fixed random seed 42), over 4653 berthing events, on a strictly uniform 8760 h grid; the port-coupling sensitivity ($\lambda \in \{0, 0.15, 0.30, 0.50\}$) changes the aggregate hourly statistics by less than ten percent, confirming the robustness of the reconstructed profile. The validation statistics in Table 2 are computed from the reconstructed and raw hourly cold-ironing profiles. The 7019 strictly non-zero reconstructed hourly records correspond to approximately 1741 fully empty hours; the slightly larger count of about 1772 near-

zero hours quoted in Sections 3.1 and 4.1 additionally includes hours whose residual cold-ironing load falls below 1 kWh.

3.3. Renewable Resource Modeling

Photovoltaic Generation. The PV generation model is based on the physical single-module representation of a commercial high-efficiency monocrystalline module (Hi-MO 9 LR8-66HYD-670M; LONGi Green Energy Technology Co., Ltd., Xi'an, China), with cell-temperature derating through the Nominal Operating Cell Temperature (NOCT) model. The cell temperature T_C is obtained from the ambient temperature T_A and the plane-of-array irradiance G (Equation (2)), and the temperature-corrected module efficiency from the standard-test-condition efficiency η_{STC} (Equation (3)):

$$T_C = T_A + \frac{NOCT - 20}{800} G \quad (2)$$

$$\eta(T_C) = \eta_{STC} [1 + \gamma(T_C - T_{STC})] \quad (3)$$

where $\eta_{STC} = 24.8\%$ is the module efficiency at standard test conditions, $\gamma = -0.26\%/^{\circ}\text{C}$ is the maximum-power temperature coefficient, $NOCT = 45^{\circ}\text{C}$, and $T_{STC} = 25^{\circ}\text{C}$ is the standard cell temperature. A constant system derating factor of 0.885 accounts for soiling, mismatch, and wiring losses. Driven by the measured on-site irradiance and temperature, the model yields an annual specific yield of approximately 1310 kWh per kW of installed capacity, corresponding to a capacity factor of 15.0%, a value consistent with a horizontal-plane fixed installation under the prevailing Mediterranean conditions of the case-study site.

Wind Generation. Wind generation is modeled by extrapolating the measured wind speed from the anemometer height z_{anem} to the turbine hub height z_{hub} through the power-law shear profile (Equation (4)):

$$V_{hub} = V_{anem} \left(\frac{z_{hub}}{z_{anem}} \right)^{\alpha} \quad (4)$$

with a shear exponent $\alpha = 0.20$ representative of coastal surface roughness. Because the available meteorological record does not document the anemometer height, a standard 10 m measurement height is assumed and an 80 m hub height is adopted for the 100–1000 kW turbine class considered here, giving a physically realistic hub-height mean wind speed of about 7.6 m/s; this assumption is revisited in the limitations (Section 5.5). The extrapolated speed is mapped to power through the normalized power curve of a 4.2 MW reference turbine (Vestas V150; Vestas Wind Systems A/S, Aarhus, Denmark), with an air-density correction for site altitude (50 m) and temperature, and an overall loss factor of 12% covering wake, electrical, and availability losses. The resulting annual specific yield is approximately 3193 kWh per kW, corresponding to a capacity factor of 36.5%. The marked contrast between the high wind capacity factor and the moderate PV capacity factor, together with their opposite seasonality, is precisely what motivates treating the PV/wind split as a decision variable rather than fixing it a priori.

3.4. Energy Storage and Hydrogen Subsystem

The storage architecture comprises two parallel subsystems whose relative sizing is determined by the GA: a lithium-ion battery energy storage system (BESS) and a hydrogen storage subsystem (H_2 -ESS) consisting of a proton exchange membrane (PEM) electrolyzer, a compressed hydrogen tank, and a PEM fuel cell.

Storage Envelope Sizing. A total storage energy envelope is first computed from the specified autonomy hours and the combined hourly port-and-CI demand series. The

envelope is the maximum, over the year, of the rolling sum of that demand across a window equal to the autonomy duration, multiplied by a design coefficient of 0.5 (so that storage covers half the worst-case window load, the remainder being met by concurrent renewable generation and the grid), and rounded up to an integer multiple of a standard 2064 kWh storage unit. The technology cost and efficiency parameters used here are collected in Table 3.

Table 3. Techno-economic parameters for HRES components and financial model.

Parameter	Value	Unit
PV CAPEX (≤ 1 kW)	1400	€/kW
PV CAPEX (> 500 kW)	600	€/kW
Wind CAPEX (≤ 50 kW)	6500	€/kW
Wind CAPEX (> 250 kW)	1500	€/kW
BESS CAPEX	480	€/kWh
Electrolyzer CAPEX	2300	€/kW
Fuel Cell CAPEX	3000	€/kW
H ₂ Tank CAPEX	1500	€/kg H ₂
BESS Round-Trip Efficiency	94	%
Electrolyzer Efficiency (HHV)	70	%
Fuel Cell Efficiency	55	%
Grid Electricity Price	0.36	€/kWh
Grid Carbon Factor	330	gCO ₂ /kWh
PV Life-Cycle Carbon Factor	37.3	gCO ₂ /kWh
Wind Life-Cycle Carbon Factor	15.0	gCO ₂ /kWh
Project Lifetime	25	years
Discount Rate	5.88	%
BESS Embodied Emissions	120,000	gCO ₂ /kWh capacity

Storage Split. The total envelope is partitioned between BESS and H₂-ESS according to a GA-optimized split ratio (BESS ratio, %). The BESS receives an energy capacity equal to the envelope multiplied by the ratio; the H₂ tank receives the remainder, converted to hydrogen mass via the lower heating value of hydrogen (33.33 kWh/kg). Electrolyzer and fuel cell power ratings are matched to the energy of the hydrogen tank through a target charge/discharge C-rate (a full tank charging over approximately eight hours and discharging over approximately four hours), bounded above by the 95th/98th percentiles of the net-load (demand minus renewable generation) surplus/deficit. This power–energy matching prevents the physically inconsistent ratings (a large fuel cell paired with a tank that would empty within an hour) produced by percentile-only sizing, and lets the genetic algorithm trade battery against hydrogen on a fair cost basis.

BESS Model. The lithium-ion BESS is modeled as a state machine with a round-trip efficiency of 94% (applied as a symmetric square-root split on charge and discharge) and minimum and maximum state-of-charge limits of 20% and 95%, respectively, so that the usable energy is the product of the installed capacity and the 20–95% state-of-charge window [4,5]. Charge and discharge power are limited to 1C (power equal to energy capacity), a limit that is non-binding for the present load. The BESS capital cost is 480 €/kWh.

H₂-ESS Model. The PEM electrolyzer operates at 70% efficiency (based on HHV), producing hydrogen at a rate proportional to input power. The PEM fuel cell operates at 55% efficiency, converting hydrogen back to electricity. The compressed hydrogen tank is sized for the required mass at 350 bar [59]. Capital costs are: electrolyzer 2300 €/kW, fuel cell 3000 €/kW, tank 1500 €/kg of H₂ capacity. The H₂-ESS life-cycle global warming

potential is computed from the embodied emissions of the electrolyzer, fuel cell, and tank, annualized over the project lifetime.

3.5. Energy Management System

The EMS applies a deterministic, priority-ordered dispatch at hourly resolution over the full 8760 h year. At each step it aggregates the photovoltaic and wind generation, computes the net load, and then either absorbs a surplus (charging the battery, then feeding the electrolyzer, then exporting to the grid) or covers a deficit (discharging the battery, then the fuel cell, then importing from the grid), recording the hourly grid exchange for the subsequent cost and emissions accounting. Figure 1 sets out this logic in full. A penalty is applied in the fitness function when annual grid exports exceed 15 percent of annual demand, discouraging configurations that grossly oversize renewable capacity relative to the port load.

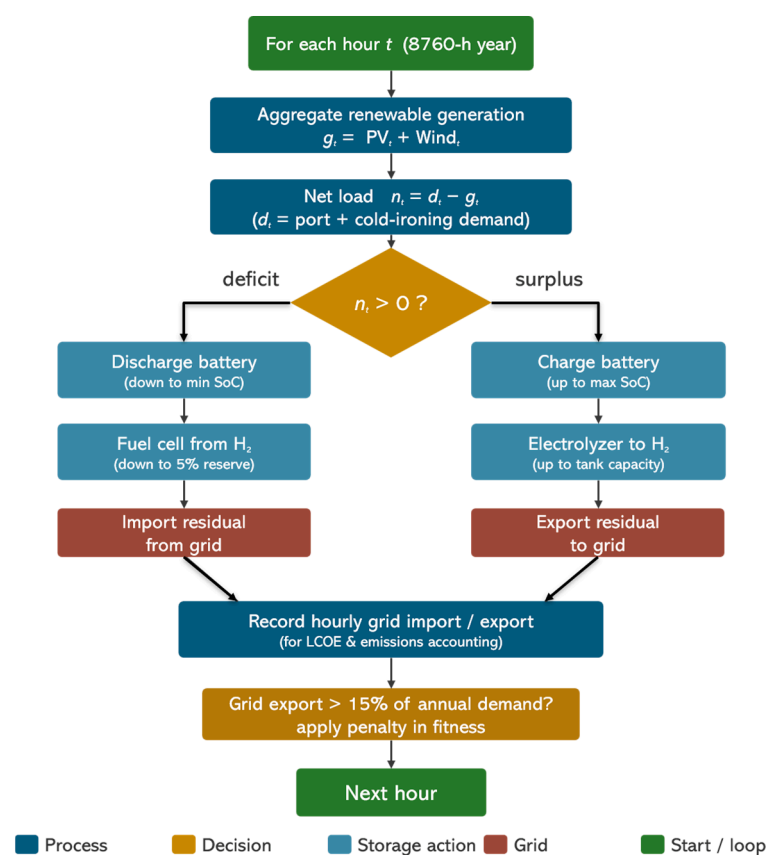


Figure 1. Hourly rule-based energy-management dispatch logic, showing the priority order (renewables, then battery, then hydrogen, then grid) for both surplus and deficit hours.

This priority order, renewables first, then battery, then hydrogen, then grid, maximizes renewable self-consumption while respecting the physical constraints of each storage subsystem. The dispatch is initialized with the battery at its minimum state of charge and the hydrogen tank half-full, and a 5% hydrogen reserve floor is maintained; the storage state is not constrained to return to its initial value at year-end, but the net annual change in stored energy is small relative to the annual demand and does not materially affect the reported balances. The deterministic logic ensures reproducibility and transparency, and the linear-time cost of its hourly dispatch pass ($O(N)$ in the number N of hourly time steps) enables its embedding within the GA loop where it is called thousands of times.

3.6. Techno-Economic Model

Table 3 summarizes the techno-economic parameters employed in the optimization and analysis.

Levelized Cost of Energy. The LCOE is computed from the net present cost and the capital recovery factor, Equation (5):

$$LCOE = \frac{NPC \times CRF}{E_{served}} \quad (5)$$

where NPC is the net present cost (total initial capital cost plus the discounted stream of grid-import costs over the project lifetime), CRF is the capital recovery factor, and E_{served} is the annual energy served. Here E_{served} is taken as the port demand plus the grid exports, consistent with treating exported renewable energy as useful system output; on the more conventional delivered-energy basis (demand only) the optimal LCOE rises from 0.283 to 0.323 €/kWh and the reduction relative to the grid-only price narrows from 21% to about 10% (exports account for 12% of the served-energy denominator). The capital recovery factor, Equation (6), is:

$$CRF = \frac{r(1+r)^N}{(1+r)^N - 1} \quad (6)$$

with discount rate $r = 5.88\%$ (taken as a representative weighted-average cost of capital for European renewable-energy infrastructure) and project lifetime $N = 25$ years; all economic indicators (LCOE, NPC, IRR, payback) are conditional on this rate, the sensitivity to which is reported in Section 4.6. Grid imports are costed at the local retail electricity price (baseline 0.36 €/kWh) and discounted to present value. The net present cost adopted here is a capital-plus-grid-energy screening estimate: it comprises the initial capital outlay and the discounted stream of grid-import costs but excludes operation-and-maintenance and mid-life component-replacement expenditures (e.g., battery or electrolyzer/fuel cell stack replacement). The reported LCOE, IRR, and payback are therefore screening-level indicators that are correspondingly favorable; incorporating O&M and replacement cash flows would raise the LCOE and lengthen the payback (Section 5.5), and is recommended before a final investment decision.

Emissions Accounting. System GHG emissions are computed as the sum of: (i) grid imports multiplied by grid carbon factor (baseline 330 gCO₂/kWh); (ii) PV generation multiplied by PV life-cycle carbon factor (37.3 gCO₂/kWh); (iii) wind generation multiplied by wind life-cycle carbon factor (15.0 gCO₂/kWh); (iv) BESS embodied emissions (120,000 gCO₂/kWh of capacity, annualized over project lifetime); and (v) H₂-ESS embodied emissions (computed from component capacities, annualized). The baseline grid-only emissions are computed as total annual demand multiplied by grid carbon factor, providing the reference against which emission reductions are measured.

Financial Metrics. Additional financial indicators are computed for the optimal configuration: net present cost, internal rate of return (IRR) relative to the grid-only baseline, and simple payback period.

3.7. Genetic Algorithm Optimization

Decision Variables. The GA operates on five integer-valued genes:

- Gene 1: PV installed capacity (kW DC), range 0–1000, step 10 kW.
- Gene 2: Wind installed capacity (kW), range 0–1000, step 20 kW.
- Gene 3: Tidal turbine units (disabled for this study, fixed at 0).
- Gene 4: Wave energy converter units (disabled for this study, fixed at 0).
- Gene 5: BESS ratio (%), range 20–80, step 1%.

Tidal and wave energy genes are disabled (fixed at zero) for the present study, which focuses on the more readily deployable PV and wind technologies for SMSPs. The BESS ratio gene determines the fraction of the total storage envelope allocated to lithium-ion battery storage, with the remainder allocated to hydrogen storage.

Fitness Function. The genetic algorithm maximizes a fitness defined as a strictly decreasing transform of a weighted-sum objective that combines the normalized levelized cost and normalized emissions, so that the fittest individuals correspond to the lowest-cost, lowest-emission configurations:

$$F = \frac{1}{1 + w_{LCOE} \cdot 10 \cdot \frac{LCOE}{LCOE_{ref}} + w_{emis} \cdot 10 \cdot \frac{E}{E_{ref}}} \cdot \frac{1}{1 + P} \quad (7)$$

where $LCOE_{ref}$ is the grid electricity price (0.36 €/kWh), E_{ref} is the grid-only annual emissions, and equal weights $w_{LCOE} = w_{emis} = 0.5$ are applied in the base case; the factor of 10 scales the two normalized terms to a comparable range. The penalty P enforces the operating constraints: a configuration whose annual grid exports exceed 15% of annual demand incurs $P = 4 \times 10^5 \cdot E_{exp} / (1.05 E_{dem})$, where E_{exp} and E_{dem} are the annual export and demand energies, and a hydrogen tank exceeding the physical-plausibility bound of 500,000 kg incurs an additional fixed $P = 10^7$; otherwise $P = 0$. Configurations whose total renewable generation exceeds 107% of annual demand are assigned zero fitness. The 15% export guard discourages configurations that oversize renewables solely to export, while the 107% cap is a coarse guard against gross over-build; both are inactive at the reported optimum (renewable generation is 76% of demand, exports are 14.2% of demand, and $P = 0$), so neither changes the headline architecture; the export guard does, however, modulate the optimal photovoltaic capacity (Section 3.8), and at the reported optimum exports settle just below the 15% cap. The fitness is evaluated on the fixed ensemble-mean cold-ironing profile of Section 3.2, and the GA is run with a fixed random seed (42 for the base case) for reproducibility; the reported optimum is obtained from this single seed, and a multi-seed robustness assessment is recommended (Section 5.5).

GA Configuration. The optimization uses a real-coded genetic algorithm implemented with the open-source PyGAD library (version 3.7.0) under Python 3.14 (Python Software Foundation, Beaverton, OR, USA); its settings are collected in Table 4. The population holds 300 candidate configurations, of which 150 are selected as parents each generation by stochastic universal sampling. Offspring are produced by single-point crossover applied to the mated parents and by random mutation at a per-gene probability of 0.15, and the 15 best individuals are carried forward unchanged (elitism). The search stops once the best fitness has not improved for 150 consecutive generations, subject to a ceiling of 700 generations; for the base case it converged after 170 generations. A fixed random seed (42) is used for the reported run, and the stability of the solution across 30 independent seeds is examined in Section 4.7. These values were not finely tuned: as Section 4.7 shows, the algorithm reaches a configuration within 0.3 percent of the global optimum obtained by exhaustively enumerating the entire discrete design space, so the search is comfortably adequate for the three-variable problem considered here.

Sustainability Indices. Beyond the primary cost and emissions objectives, five composite indices are reported for each configuration as transparent, adjustable multi-criteria decision aids rather than validated metrics. They summarize, on comparable scales, the economic, environmental, social, technological, and political dimensions that port operators weigh alongside cost and carbon, following the established practice of composite sustainability indicators in energy-system assessment [36,78,83]. Their definitions, weights, and base-case values are collected in Table 5; the weights are illustrative and user-adjustable, and the indices are intended only for relative comparison across candidate configurations,

not for absolute interpretation. In particular, the Economic Index is a monotone transform of the levelized cost and carries no independent cost–benefit information.

Table 4. Genetic-algorithm configuration used for all optimizations in this study.

Setting	Value
Decision variables	PV 0–1000 kW (step 10); wind 0–1000 kW (step 20); battery ratio 20–80% (step 1); tidal/wave fixed at 0
Population size	300
Parents per generation	150
Parent selection	Stochastic universal sampling
Crossover	Single-point (applied to mated parents)
Mutation	Random, per-gene probability 0.15
Elitism	15 best individuals retained
Termination	150 generations without improvement (ceiling 700); converged at 170
Fitness penalties	Grid export > 15% of demand: coefficient 4×10^5 ; hydrogen tank > 5×10^5 kg: 10^7
Random seed	42 (base case); 30 seeds for robustness (Section 4.7)

Table 5. Definitions, weights, and base-case values of the five sustainability indices (heuristic, user-adjustable multi-criteria decision aids, not validated metrics).

Index	Definition	Base-Case Value
Economic (EII)	$1/(1 + \text{LCOE})$; decreasing in the levelized cost of energy	0.78
Environmental (EnvII)	Percentage greenhouse-gas reduction versus the grid-only baseline	44.8%
Social (SII)	$0.6 \times \text{renewable penetration (\%)} + 0.3 \times \text{storage share (\%)} - 0.1 \times \text{grid export (\%)}$	54.0
Technological (TII)	$0.25 \times \text{TDS} + 0.15 \times \text{ETF} + 0.20 \times \text{DSF} + 0.20 \times \text{storage share} + 0.20 \times \text{renewable penetration}$, with technology-diversity score TDS, emerging-technology factor ETF and deployment-scale factor DSF	0.39
Political (PII)	Weighted supply-source shares ($0.30 \text{ wind} + 0.20 \text{ PV} + 0.10 \text{ battery} + 0.05 \text{ fuel cell} - 0.20 \text{ grid}$), as percent, clamped to the range 0 to 100	6.4

3.8. Scenario Definition and Sensitivity Analysis

Because the storage envelope is itself a design decision, the storage autonomy is treated as a swept sizing parameter: the framework performs an independent GA optimization at each of several storage-autonomy levels (0, 4, 8, and 12 h), where an autonomy of zero corresponds to a grid-connected renewable system with no storage and larger values size progressively larger storage envelopes (the envelope being computed as 50% of the maximum rolling demand over the autonomy window, rounded up to integer multiples of the standard storage unit). Comparing the GA-optimal configurations across these levels exposes the cost–emissions trade-off and identifies the economically and environmentally balanced design. The base optimization scenario adopts an 8 h autonomy together with equal LCOE/emissions weights, grid cost 0.36 €/kWh, grid carbon factor 330 gCO₂/kWh, discount rate 5.88%, and project lifetime 25 years. In addition, single-parameter sensitivity analyses vary the discount rate (3%, 5.88%, 8%), the grid carbon factor (150, 330, 500 gCO₂/kWh), the grid electricity price (0.20, 0.36, 0.50 €/kWh), and the demand scaling (80%, 100%, 120% of baseline); each is run as an independent GA optimization, and the resulting optimal configurations and objective values are compared.

Provenance of model parameters. Table 6 records the origin and evidential basis of the parameters that are set rather than optimized. The demand-model coupling, noise, and autocorrelation parameters are class-level operational assumptions of the stochastic reconstruction, not fitted values; the reconstruction conserves each vessel class’s annual energy exactly regardless of their setting, and a dedicated sensitivity study confirms that

the aggregate hourly statistics vary by less than ten percent across the full range of port-coupling strengths. The objective weighting and the export-penalty settings are shown, through the re-optimizations reported below, to leave the optimal configuration either unchanged or shifted only in a smooth, interpretable way, as recorded in Table 6.

Table 6. Provenance and evidential basis of the model parameters that are set rather than optimized.

Parameter	Value(s)	Role	Basis and Evidence
Port-coupling λ (per vessel class)	0.18–0.30	Elasticity of ship load to the standardized port-activity signal	Class-level operational assumption; scheduled ferries/cargo couple more tightly than irregular calls; aggregate statistics vary <10% across λ from 0 to 0.5
Intra-call noise σ (per class)	0.12–0.18	Amplitude of within-call variability	Coefficient-of-variation of an AR(1) log-normal multiplier bounded to [0.55, 1.65]; does not affect exact energy conservation
Autocorrelation ρ (per class)	0.35–0.60	Hour-to-hour persistence of the noise	Standard stationary first-order autoregressive process; reproduces realistic persistence
Objective weight (LCOE: emissions)	0.5:0.5	Scalarization of the two objectives	Equal a priori preference; optimum invariant for weights 0.3–0.7 (re-optimized)
Export-penalty threshold	15% of annual demand	Discourages export-oriented oversizing	Typical interconnection export ceiling; PV shifts from 330 to 430 kW over 10–20% while the architecture is unchanged
Export-penalty coefficient	4×10^5	Strength of the soft export penalty	Inactive at the optimum; result invariant for 10^5 – 10^6
GA population/generations	$300 \leq 700$	Search breadth and budget	Reaches within 0.3% of the exhaustive global optimum (Section 4.7)

4. Results

4.1. Cold Ironing Demand Profile

The PC-ECSD v3 model transforms the sparse call-level records into a continuous hourly demand profile while conserving annual energy exactly (Table 2). The total annual port energy demand is approximately 657 MWh, comprising a terrestrial baseline of 70.4 MWh and a cold ironing load of 587 MWh; the CI component thus contributes 89% of the annual total. The reconstructed hourly CI demand is extremely variable: the combined peak reaches approximately 584 kW during summer multi-vessel berthing, while the median hourly demand is only 38 kW and the cold ironing load is below 1 kWh for about 20% of the year.

The annual demand profile (Figure 2) presents the daily energy as a stacked area chart, with the port baseline in the lower band and the ship CI demand above. The profile is dominated by a strong May–October peak that coincides with the cruise and high-tourism season, daily CI energy approaches or exceeds 3000 kWh in July and August, reaching about 4500 kWh on the busiest days, and falls to a low winter level of a few hundred kWh per day. Multi-day intervals of zero CI demand are visible throughout the off-season, a characteristic that fundamentally differentiates the CI load from conventional municipal or industrial loads and that, as shown below, makes solar PV the naturally dominant resource for this demand shape.

The hourly heatmap (Figure 3) reveals the joint seasonal–diurnal structure of the load. High-intensity cells concentrate in the summer months across the daytime and evening hours that correspond to typical arrival and departure schedules, while the winter months show a diffuse, low-intensity pattern. The heatmap confirms that CI demand is neither uniform across the year nor across the diurnal cycle, underscoring the necessity of hourly resolution modeling for accurate sizing.

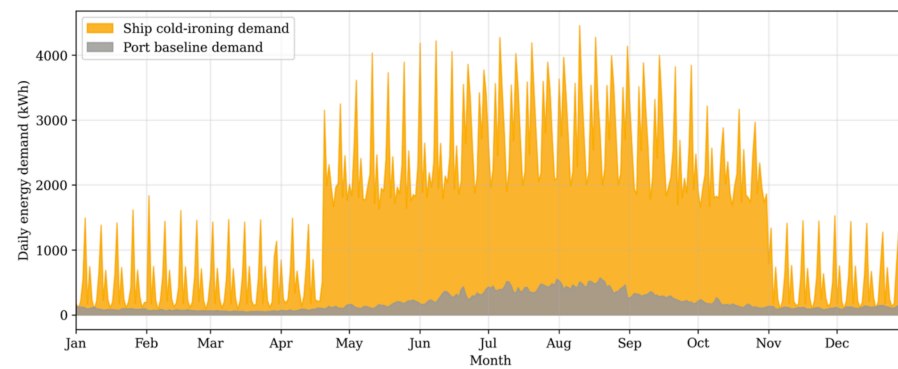


Figure 2. Annual port energy demand profile with stacked daily components (port baseline and ship cold ironing).

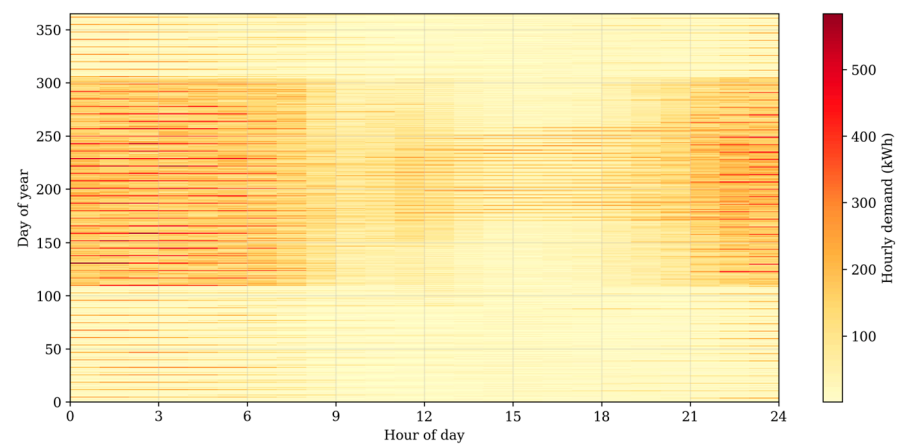


Figure 3. Hourly heatmap of the combined port-and-cold-ironing demand (kW) across day of year (vertical) and hour of day (horizontal).

The load duration curve (Figure 4) ranks all 8760 hourly values in descending order and exposes the extreme peak-to-average character of the load. Demand exceeds 223 kW (the 95th percentile) for only the top 5% of hours, while the median is 38 kW; the curve descends steeply from the 584 kW peak. Any system sized to the absolute peak would operate at a small fraction of its capacity for most of the year, which is precisely why storage and grid interaction, rather than pure renewable oversizing, are the rational means of managing the peak.

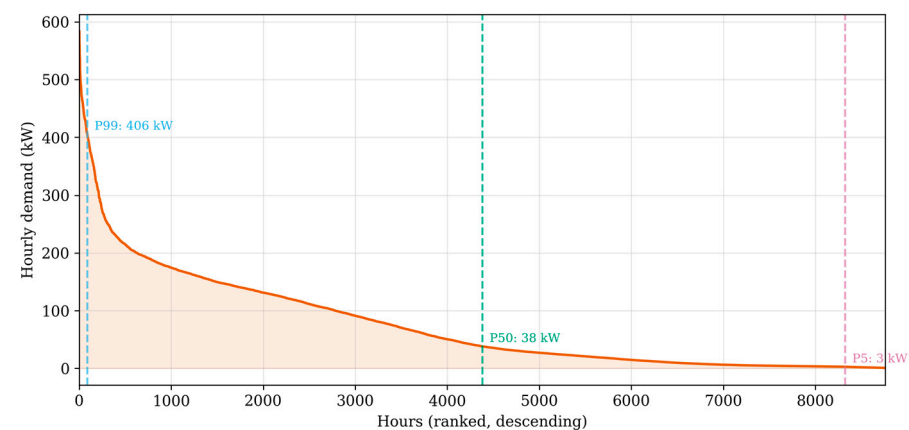


Figure 4. Load duration curve of the combined port-and-CI demand with percentile annotations.

The solid orange curve is the hourly demand ranked in descending order, with the area beneath it shaded; the blue, green and pink dashed vertical lines mark the 99th, 50th and 5th percentiles of the hourly demand, at 406, 38 and 3 kW, respectively.

4.2. Optimal Configuration and the Cost–Emissions Trade-Off

The framework optimizes the storage envelope jointly with the renewable mix: for each candidate storage autonomy the genetic algorithm searches the PV, wind, and battery-ratio space, and the resulting configurations trace a clear cost–emissions trade-off (Table 7, Figure 5). With no storage, the cost-minimizing solution is a small grid-connected PV–wind system (80 kW PV, 40 kW wind) that lowers the levelized cost of energy (LCOE) to 0.282 €/kWh, a 22% reduction relative to the grid-only price of 0.36 €/kWh, but achieves only an 18% emission reduction, because without storage the summer midday PV surplus cannot be shifted to the evening demand peak. Introducing a storage autonomy of 4–8 h raises the emission reduction to 45% while keeping the LCOE essentially unchanged at 0.283 €/kWh, and a 12 h autonomy deepens the emission reduction to 52% at an LCOE of 0.365 €/kWh, marginally above grid parity. The 8 h autonomy configuration is adopted as the base case because it sits at the knee of this trade-off, delivering deep decarbonization at an LCOE that remains below the grid price.

Table 7. Cost–emissions trade-off across storage autonomy (each row is an independent GA optimization). LCOE values are reported on the served-energy basis (Section 3.6); on a delivered-energy basis they are higher (e.g., 0.323 €/kWh for the base case).

Storage Autonomy (h)	PV (kW)	Wind (kW)	Storage Envelope (kWh)	LCOE (€/kWh)	Grid Import (%)	Emission Reduction (%)
0	80	40	0	0.282	79.0	18.3
4	380	0	2064	0.283	43.0	44.8
8 (base)	380	0	2064	0.283	43.0	44.8
12	440	0	4128	0.365	30.7	52.2

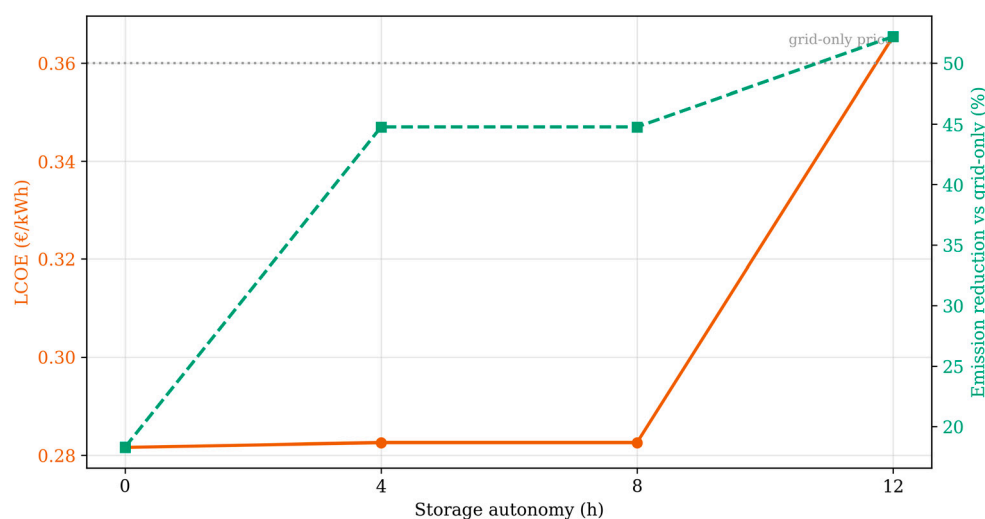


Figure 5. Storage-autonomy cost–emissions trade-off: LCOE and emission reduction versus storage autonomy. The solid orange line with circular markers is the LCOE (left axis) and the dashed green line with square markers the emission reduction relative to grid-only supply (right axis); the dotted grey line marks the grid-only price of 0.36 €/kWh.

The genetic algorithm converges within about 170 generations (Figure 6), after which the best fitness no longer improves. The base-case optimal configuration is summarized

in Table 8. The blue curve is the best fitness reached up to each generation, with the area beneath it shaded; the annotation marks the generation at which the run converged.

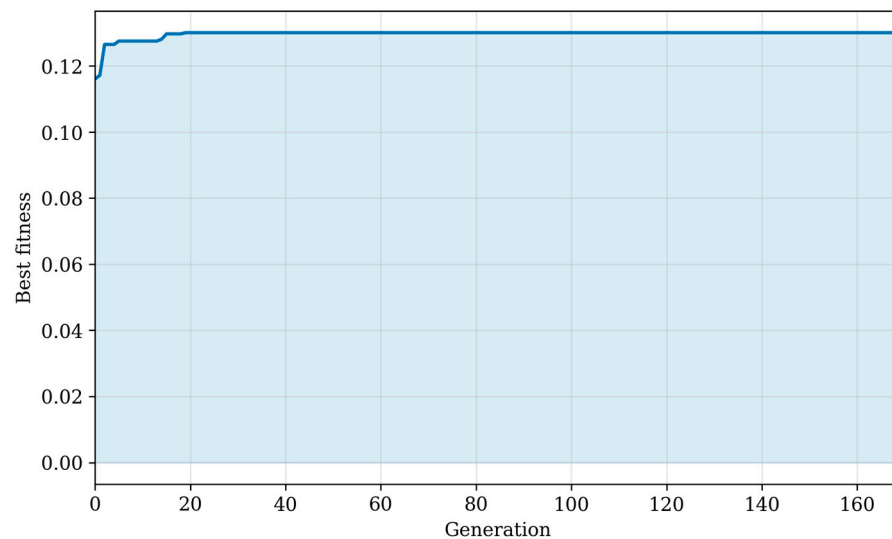


Figure 6. GA convergence: best fitness versus generation for the base-case optimization.

Table 8. Base-case optimal HRES configuration determined by the genetic algorithm (8 h storage autonomy).

Parameter	Optimal Value	Unit
PV installed capacity	380	kW
Wind installed capacity	0	kW
BESS ratio	79	%
Total storage envelope	2064	kWh
BESS energy capacity	1631	kWh
H ₂ tank capacity	13.0	kg H ₂
Electrolyzer power	77	kW
Fuel cell power	60	kW
Total capital cost	1.42	M€
Net present cost	2.74	M€
LCOE	0.283	€/kWh
Annual GHG emissions	120	tCO ₂ eq/yr
Emission reduction vs. grid-only	45	%
HRES penetration	76	%
Non-grid supply fraction	57	%
IRR	8.1	%
Simple payback period	10.6	years

For this case study the optimizer allocates the renewable capacity almost entirely to PV (380 kW) and selects no wind in the storage-backed base case. This is a direct consequence of the demand shape: cold ironing demand is strongly summer-peaked, and PV generation, also summer-peaked, is therefore exceptionally well matched to it, so that PV energy is largely self-consumed. The wind resource, although of high quality (36.5% capacity factor), is winter-biased and temporally mismatched to the summer demand, so additional wind capacity would be exported (and penalized) rather than consumed. Wind nevertheless enters the cost-optimal storage–light configuration (Table 7, 0 h autonomy), where, in the absence of storage, its temporal diversity partially substitutes for time-shifting. The storage selected by the GA is battery-dominant (79% lithium-ion/21% hydrogen), reflecting the

superiority of high-efficiency battery cycling for the predominantly diurnal mismatch of this load, with a small hydrogen subsystem retained for longer-duration buffering.

4.3. Energy Balance and Grid Interaction

Under the base-case configuration and the rule-based EMS, the annual energy balance is: PV generation 498 MWh/yr, battery discharge 209 MWh/yr, fuel cell discharge 10 MWh/yr, and grid import 283 MWh/yr; grid export totals 93 MWh/yr. The renewable penetration (renewable generation relative to demand) is 76%, while 57% of the served energy is supplied without recourse to the grid.

The monthly energy mix (Figure 7) shows PV generation tracking the demand seasonality, supplying the bulk of the load in the high-demand summer months, with grid import rising in the same months only because the absolute demand is highest then. The winter months are met almost entirely from PV and stored energy because the absolute demand is small.

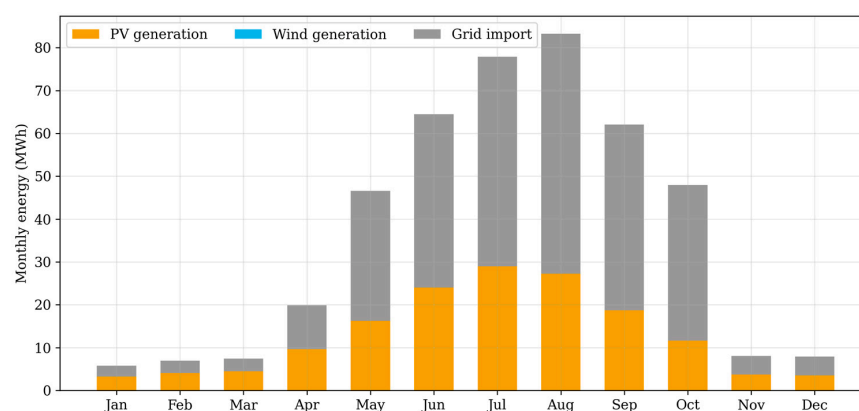


Figure 7. Monthly energy mix showing the photovoltaic and grid contributions to monthly demand (the base-case optimum includes no wind capacity).

The annual energy-balance breakdown (Figure 8) displays the contribution of each supply source. PV generation provides the dominant share, battery discharge contributes the stored-renewable component that covers the evening demand peak, and grid import (43% of demand) serves as the residual reliability source. The balance confirms that the optimized system achieves substantial grid displacement while retaining the grid as a backstop rather than eliminating it.

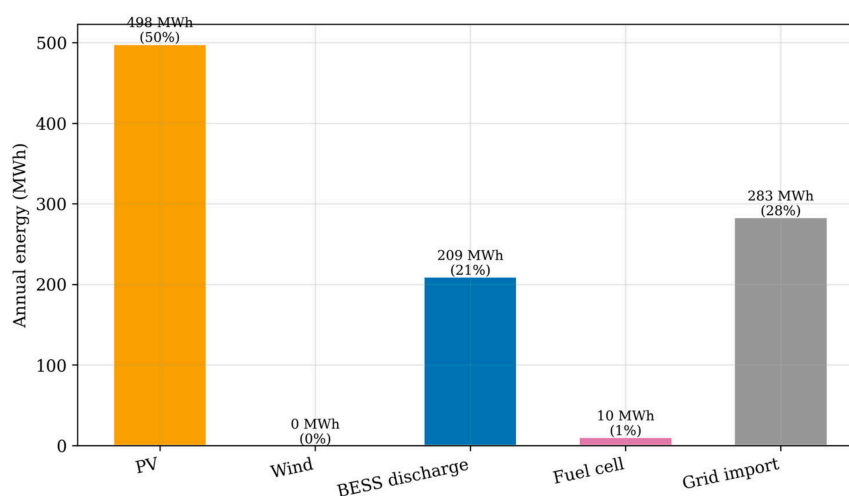


Figure 8. Annual energy supplied (MWh/yr) by source: PV generation, battery discharge, fuel cell discharge, and grid import.

4.4. Economic and Environmental Performance

The LCOE of the optimal configuration is 0.283 €/kWh on the served-energy basis, a 21% reduction relative to the grid-only baseline of 0.36 €/kWh (on the conventional delivered-energy basis the figures are 0.323 €/kWh and a 10% reduction; see Section 3.6). The system net present cost is 2.74 M€, against a grid-only NPC of 3.06 M€ (the discounted cost of 25 years of grid purchases for the full port demand). The configuration yields an internal rate of return of 8.1% relative to the grid-only baseline and a simple (undiscounted) payback period of 10.6 years, approximately 17 years on a discounted basis at the 5.88% rate, on a total capital outlay of 1.42 M€; as noted in Section 3.6, these indicators exclude operation-and-maintenance and component-replacement costs and are therefore screening-level estimates.

Annual system GHG emissions are 120 tCO₂eq/yr, compared with 217 tCO₂eq/yr for the grid-only baseline, a 45% reduction. The emissions are dominated by the residual grid imports (93 tCO₂eq/yr), followed by PV life-cycle emissions (19 tCO₂eq/yr) and the annualized embodied emissions of the battery (8 tCO₂eq/yr); the hydrogen subsystem contributes negligibly.

The emissions comparison (Figure 9) contrasts three scenarios: auxiliary engines (vessels operating onboard diesel generators at berth), grid-only CI (all energy purchased from the grid), and the optimized HRES-CI configuration. The auxiliary-engine scenario emits 428 tCO₂eq/yr, based on an at-berth marine-diesel emission factor of 690 gCO₂/kWh applied to the CI load (with the port baseline drawn from the grid). The grid-only CI scenario emits 217 tCO₂eq/yr at the grid carbon factor of 330 gCO₂/kWh. The HRES-CI configuration emits 120 tCO₂eq/yr, a 72% reduction relative to auxiliary engines and a 45% reduction relative to grid-only CI, while additionally eliminating the local SO_x, NO_x, and particulate emissions of at-berth combustion.

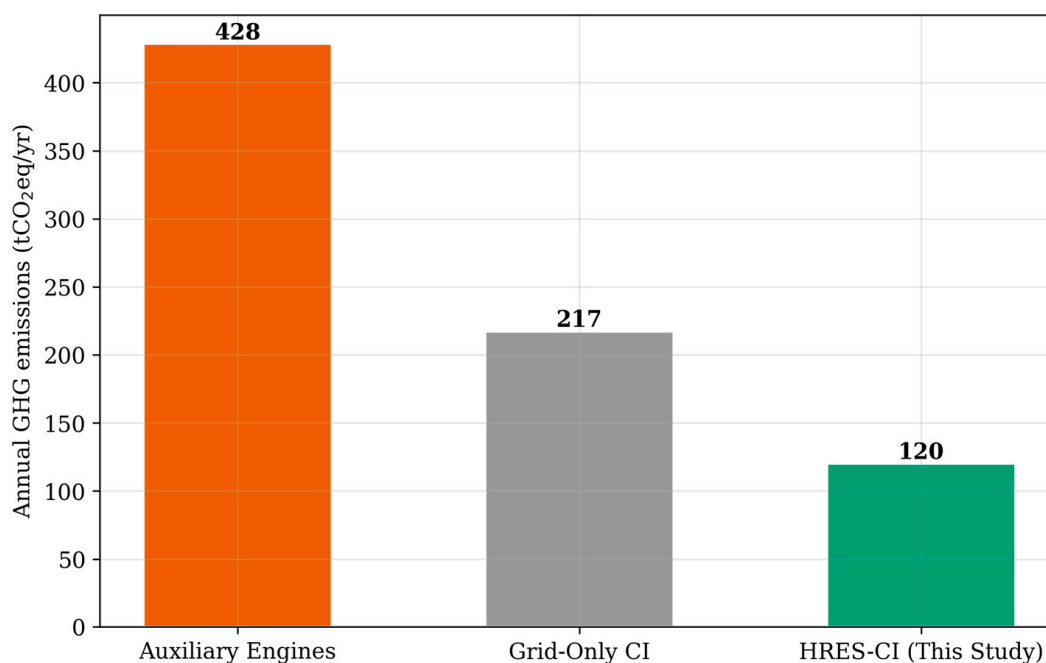


Figure 9. Annual GHG emissions (tCO₂eq/yr) for three at-berth supply scenarios: auxiliary engines (428), grid-only cold ironing (217), and the optimized HRES-CI configuration (120).

4.5. Sustainability Indices

The five sustainability indices for the base-case configuration are: Economic Index (EII) 0.78; Environmental Index (EnvII) 44.8% (emission reduction); Social Index (SII) 54.0;

Technological Index (TII) 0.39; and Political Index (PII) 6.4. The high EII reflects the sub-grid LCOE; the moderate SII captures the substantial renewable penetration together with the retained 43% grid dependence; and the low PII results from the predominantly grid-and-PV supply mix with limited technology diversity. These indices use illustrative, non-validated weights and are intended only for relative comparison across candidate configurations, not for absolute interpretation; in particular, the Economic Index is a monotone transform of the LCOE and carries no independent cost–benefit information. With that caveat, they provide port operators with a multi-dimensional view of configuration performance beyond the primary LCOE and emissions metrics.

4.6. Sensitivity Analysis

Table 9 reports the sensitivity of the optimal configuration and its performance to four key parameters, each re-optimized independently.

Table 9. Sensitivity analysis: effect of parameter variation on the optimal configuration and performance.

Parameter Varied	Value	PV (kW)	Wind (kW)	LCOE (€/kWh)	Grid Import (%)	Emission Reduction (%)
Discount rate	3%	380	0	0.245	43.0	44.8
Discount rate	5.88% (base)	380	0	0.283	43.0	44.8
Discount rate	8%	380	0	0.314	43.0	44.8
Grid carbon factor	150 gCO ₂ /kWh	380	0	0.283	43.0	30.1
Grid carbon factor	330 gCO ₂ /kWh (base)	380	0	0.283	43.0	44.8
Grid carbon factor	500 gCO ₂ /kWh	380	0	0.283	43.0	48.9
Grid price	0.20 €/kWh	380	0	0.222	43.0	44.8
Grid price	0.36 €/kWh (base)	380	0	0.283	43.0	44.8
Grid price	0.50 €/kWh	380	0	0.335	43.0	44.8
Demand scale	80%	330	0	0.295	36.9	49.3
Demand scale	100% (base)	380	0	0.283	43.0	44.8
Demand scale	120%	530	0	0.326	31.3	52.9

The tornado diagram (Figure 10) ranks the parameters by their influence on LCOE. The discount rate and the grid electricity price produce the widest LCOE ranges, the former through the present-value weighting of capital against future grid purchases, the latter through the cost of residual grid import. The grid carbon factor leaves the LCOE essentially unchanged, the optimal renewable mix is robust to it, but strongly governs the achievable emission reduction, which rises from 30% in an already-decarbonized grid (150 gCO₂/kWh) to 49% in a carbon-intensive grid (500 gCO₂/kWh). The demand-scaling sensitivity shows that the methodology produces approximately proportional sizing recommendations, increasing the optimal PV capacity from 330 kW at 80% demand to 530 kW at 120% demand. Two practically significant findings emerge. First, the optimal configuration is robust: across all economic perturbations the GA retains the PV-plus-battery architecture and a 43% grid-import share, never converging to a fully off-grid solution. Second, the emission-reduction potential is governed almost entirely by the grid carbon factor, so that the environmental value of the investment is greatest precisely where the local grid remains carbon-intensive, as is still the case in several Mediterranean systems.

Each bar spans the LCOE range obtained when the parameter is varied over the range given in its label, all other parameters held at their base-case values; blue denotes values below and orange values above the base-case LCOE of 0.283 €/kWh (vertical line). The grid carbon factor shows no bar because it leaves the LCOE unchanged.

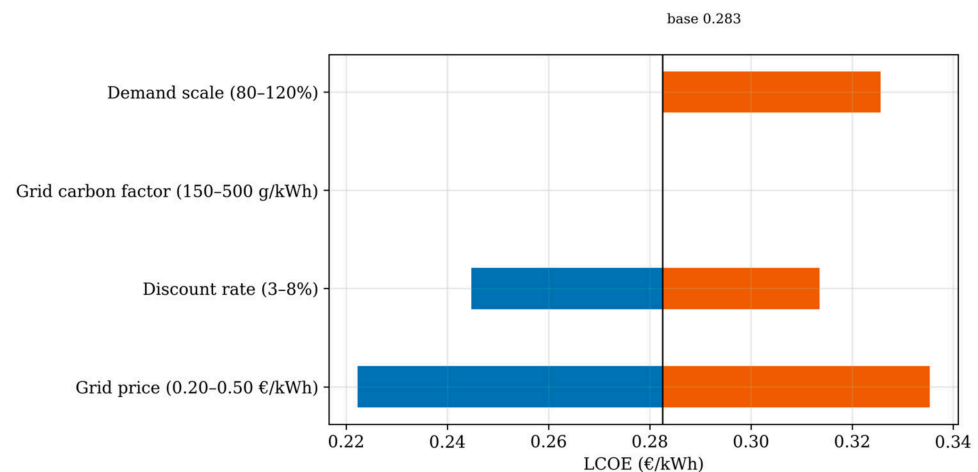


Figure 10. LCOE sensitivity tornado diagram for the key parameters.

4.7. Optimizer Benchmarking, Robustness, and Full Life-Cycle Economics

Optimizer benchmarking. To confirm that the reported configuration is a genuine optimum rather than an artifact of the genetic algorithm, the base-case problem, at the fixed base-case storage envelope, was solved three ways on the identical objective: by exhaustively enumerating all 314,211 configurations of the three-variable design space (photovoltaic capacity, wind capacity and battery-to-hydrogen ratio); by the genetic algorithm of Table 7 across 30 independent random seeds; and by a standard global-best particle swarm optimizer (a swarm of 60, constriction coefficients $w = 0.73$ and $c_1 = c_2 = 1.50$, velocity clamped to one-fifth of the search range [84,85]) across 30 seeds. Both metaheuristics used the same early-stopping rule (150 iterations without improvement, subject to a hard cap), so the comparison is one of efficiency to a common convergence criterion rather than of a fixed evaluation count.

Table 10 and Figure 11 summarize the results. Exhaustive enumeration locates the global optimum, over this three-variable space, at 380 kW of photovoltaics, no wind and an 80 percent battery ratio; the particle swarm optimizer reaches it in all 30 runs, and the genetic algorithm converges to the adjacent 79 percent-battery design, whose fitness and levelized cost lie 0.27 and 0.44 percent from the optimum (the corresponding mean gaps across the 30 seeds are 0.34 and 0.64 percent; Table 10).

Table 10. Benchmarking of the genetic algorithm against exhaustive enumeration and a particle swarm optimizer on the identical base-case problem (30 independent seeds each; mean $\pm$ standard deviation).

Method	Best Design (PV/Wind/Battery Ratio)	Best Fitness	LCOE (EUR/kWh)	Fitness Evaluations	Runtime (s)	Reaches Global Optimum
Exhaustive enumeration	380/0/80%	0.13045	0.2813	314,211	7.3	ground truth
Particle swarm (30 seeds)	380/0/80%	0.13045 $\pm$ 0	0.2813 $\pm$ 0	9944 $\pm$ 1002	1.84 $\pm$ 0.12	30/30
Genetic algorithm (30 seeds)	380/0/79%	0.13001 $\pm$ 0.00034	0.2831 $\pm$ 0.0022	23,966 $\pm$ 4911	4.19 $\pm$ 0.78	within 0.27% of optimum

All three methods therefore agree on the headline architecture, maximal cost-effective photovoltaics with battery-dominant storage, confirming that the reported configuration is effectively optimal for the problem solved. Efficiency is measured primarily by fitness evaluations, of which the particle swarm optimizer used about 9900 and the genetic algorithm about 24,000; the corresponding run times on an Intel Core i5-14600K workstation (Intel Corporation, Santa Clara, CA, USA; 64 GB RAM, Windows 11), 1.8 s and 4.2 s, share

the same per-evaluation model implementation and are therefore indicative rather than a like-for-like optimizer speed comparison, and both are far quicker than the 7.3 s exhaustive search. Enumeration is tractable here only because the reduced three-variable space is small; the genetic algorithm is retained as the framework's optimizer because it is the one method of the three that remains practical once the full design space is restored, reinstating the tidal and wave technologies and refining the capacity grid, where the number of configurations grows by orders of magnitude and enumeration becomes infeasible. The base case therefore serves as a ground-truth validation of the optimizer, not as the limit of its applicability.

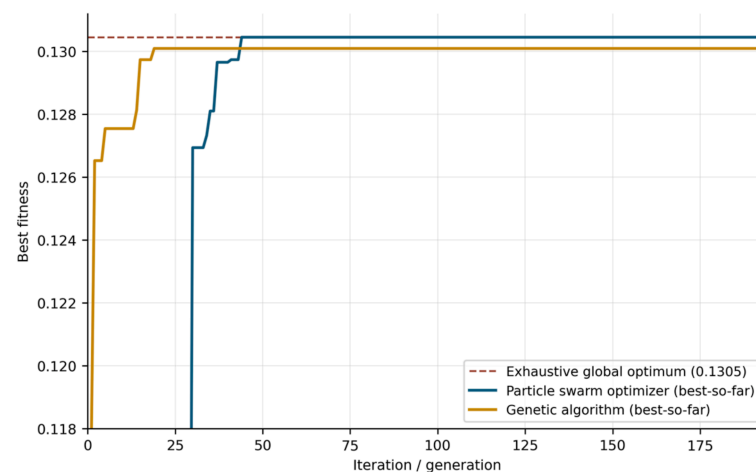


Figure 11. Convergence of the genetic algorithm and the particle swarm optimizer (best fitness so far) toward the exhaustively enumerated global optimum for the base-case problem.

Storage-technology preference. Because the battery-to-hydrogen ratio was bounded at 80 percent battery, the optimum above is pinned at that bound, so the small hydrogen fraction it implies is the residual of the bound rather than a cost-driven selection. Relaxing the bound to 100 percent battery and re-enumerating confirms this directly: fitness increases monotonically with battery share, and the unconstrained cost-optimum is essentially pure battery (a 99–100 percent battery ratio), which lowers the levelized cost from 0.283 to about 0.258 EUR/kWh. This is expected, since the battery round-trip efficiency (94 percent) far exceeds that of the electrolyzer–fuel-cell path (about 39 percent) with no offsetting cost advantage per delivered kilowatt-hour, so for the predominantly diurnal mismatch of this summer-peaked load high-efficiency battery storage is unambiguously preferred. The base-case design retains a 20 percent hydrogen floor as a deliberate provision for longer-duration reserve during the multi-day vessel-free intervals of the off-season, at a modest cost premium; absent that requirement, a pure-battery configuration is recommended. The value of treating the storage split as a decision variable is therefore that the framework reveals which technology dominates, here battery, rather than presupposing a mix: a hydrogen fraction is justified on cost grounds only for ports whose cold-ironing mismatch is genuinely multi-day or seasonal.

Optimizer robustness. Across the 30 independent seeds the genetic algorithm selected 380 kW of photovoltaics in 28 runs (330 kW in the other two) and the 79 percent battery ratio in every run, giving a levelized cost of 0.283 ± 0.002 EUR/kWh on the served-energy basis (95 percent confidence interval ± 0.001) and an emission reduction of 44.8 ± 0.2 percent. The headline design is therefore reproducible across seeds rather than the product of a single fortunate run and, as the benchmarking above shows, sits within 0.3 percent of the exhaustively verified global optimum.

Isolating the storage effect. Because each storage-autonomy level in Section 4.2 co-scales the renewable capacity with the storage envelope, an additional experiment held

the PV capacity fixed at the 8 h optimum (380 kW, no wind) and swept only the storage envelope (Table 11). With renewable capacity held constant, the emission reduction rises from 15% with no storage to 36% at 1032 kWh and 45% at 2064 kWh, saturating near 47% at 3096 kWh before declining slightly as the embodied emissions and round-trip losses of an oversized battery begin to dominate. This isolates the storage contribution from the RE scale-up and confirms directly that storage, not additional renewable capacity, drives the deep emission cuts: at a fixed 380 kW of PV, storage alone triples the emission reduction.

Table 11. Isolated storage sweep at fixed PV (380 kW, no wind, 79% battery ratio): only the storage envelope is varied. LCOE is on the served-energy basis (Section 3.6).

Storage Envelope (kWh)	LCOE (€/kWh)	Grid Import (%)	Emission Reduction (%)
0	0.201	76.4	15.0
1032	0.234	54.0	35.6
2064 (base)	0.283	43.0	44.8
3096	0.339	38.7	47.3
4128	0.398	37.9	46.3

Full life-cycle economics. The net present cost in Section 3.6 is a capital-plus-grid-energy screening estimate. To bound the investment case under more realistic costs, the base optimum was re-costed with annual operation-and-maintenance (O&M) expenditure, expressed as a fraction of capital, and a single mid-life replacement (at year 13) of the battery, at 60% of its current unit cost, reflecting projected battery-cost declines, and of the hydrogen stacks (Table 12). Adding O&M at 1.5%/yr together with the mid-life replacement raises the delivered-energy LCOE from the screening value of 0.323 to about 0.39 €/kWh, roughly 8% above the grid price, lowers the internal rate of return from 8.1% to about 3.8% (below the assumed 5.88% cost of capital, implying a negative net present value), and extends the simple payback to about 18 years, with the discounted payback exceeding the 25-year project life. A conservative case (2%/yr O&M and full-cost replacement) gives an LCOE roughly 17% above grid and an IRR near 1%. The headline economic indicators are therefore best read as screening-level figures: the configuration is competitive with the grid on energy cost alone, but on a full life-cycle basis at current battery costs the investment is marginal-to-uneconomic, and its value rests increasingly on its deep decarbonization and the elimination of local air pollutants. The case improves materially with the battery-cost declines projected over the investment horizon and with any capital-support mechanism, and is most attractive where the displaced grid is carbon-intensive.

Table 12. Full life-cycle economics of the base optimum under operation-and-maintenance (O&M, as a fraction of capital per year) and one mid-life (year 13) replacement of the battery and hydrogen stacks. LCOE is on the delivered-energy basis; “Difference vs. Grid” is the difference from the 0.36 €/kWh grid price (negative = below grid); payback is from the avoided grid-cost stream net of O&M.

Cost Scenario	LCOE (€/kWh)	Difference vs. Grid (%)	IRR (%)	Payback, Simple (yr)	Payback, Discounted (yr)
Screening (Sections 3.6 and 4.4)	0.323	−10	8.1	10.6	~17
+O&M 1.0%/yr	0.344	−4	6.8	11.8	~21
+O&M 1.5%, battery + H ₂ replacement	0.390	+8	3.8	18.0	>25
Conservative (O&M 2.0%, full-cost replacement)	0.420	+17	1.4	22.5	>25

5. Discussion

5.1. Principal Findings and Their Significance

The results demonstrate that a grid-connected HRES with GA-optimized sizing and a rule-based EMS can simultaneously reduce the levelized cost of energy and the carbon footprint of cold ironing at a representative Mediterranean SMSP. The base-case configuration achieves an LCOE reduction of about 10% on a delivered-energy basis (0.323 vs. 0.36 €/kWh), or 21% when exported renewables are credited (0.283 €/kWh), together with a 45% emission reduction (120 vs. 217 tCO₂eq/yr), an internal rate of return of 8.1%, and a 10.6-year simple payback (about 17 years discounted) on a capital-plus-grid-energy screening basis. These figures establish that renewable-powered CI is competitive with the grid at the screening level and delivers deep decarbonization for the SMSP segment, which the literature identifies as facing the most acute deployment barriers [12,23]; as Section 4.7 shows, however, its full life-cycle economics, once operation, maintenance, and a mid-life battery replacement are included, are marginal at current battery costs, so the investment case rests substantially on the value of decarbonization and on projected battery-cost declines.

Table 13 summarizes the principal findings and the quantitative evidence for each, condensing the comparisons that follow.

Table 13. Summary of the principal findings and the quantitative evidence for each.

Finding	Quantitative Evidence	Section
Renewable-powered cold ironing is competitive at the screening level	LCOE 0.283 EUR/kWh served (0.323 delivered) vs. 0.36 grid; IRR 8.1%; 10.6-yr payback	4.4
Competitiveness is marginal on a full life-cycle basis	With O&M and one battery replacement, LCOE~grid parity, IRR ~ 4%	4.7
The optimal mix follows demand seasonality	380 kW PV, 0 kW wind for summer-peaked cruise demand	4.2
Storage, not renewable oversizing, drives decarbonization	At fixed 380 kW PV, storage lifts the emission cut from 15% to 45%	4.7
Battery storage dominates the cost-optimal design	Unconstrained optimum is essentially pure battery; base case retains 21% hydrogen as reserve	4.7
Emission reduction is governed by grid carbon intensity	30% at 150 gCO ₂ /kWh rising to 49% at 500 gCO ₂ /kWh	4.6
The design is effectively globally optimal (three-variable space)	Within 0.27% of the exhaustive optimum; particle swarm agrees	4.7

A central and non-obvious finding is that, for this demand profile, the cost-optimal renewable resource is solar PV rather than a balanced PV–wind mix, despite the high quality of the local wind resource. The explanation lies in the temporal structure of cold ironing demand: it is strongly summer-peaked, driven by the cruise and high-tourism season, and PV generation, also summer-peaked, is therefore exceptionally well matched to it. Wind generation, although abundant, is winter-biased and temporally misaligned with the summer demand, so additional wind capacity would be exported rather than self-consumed. This result does not diminish the value of treating PV and wind jointly; on the contrary, it vindicates it. The framework does not presuppose a resource mix but discovers the one appropriate to each port’s demand shape: for a summer-peaked cruise port PV dominates, whereas a winter-baseload-dominated cargo or ferry port would draw the optimum toward wind. Indeed, wind re-enters the optimum in the storage–light configuration, where its temporal diversity substitutes for the time-shifting that storage would otherwise provide.

A second central finding is that storage-backed configurations, rather than renewable oversizing beyond demand, are the lever for deep decarbonization of a grid-connected CI system. Although each autonomy level in the trade-off co-scales the renewable capacity

with the storage envelope, the isolated storage sweep of Section 4.7, which holds the PV capacity fixed at 380 kW and varies only the storage, confirms the attribution directly: at constant renewable capacity, adding storage raises the emission reduction from 15% to 45%. The cost–emissions trade-off (Table 7, Figure 5) shows that a storage–light system already captures the low-hanging LCOE reduction but only an 18% emission cut, whereas an 8 h storage envelope raises the emission reduction to 45% at essentially the same LCOE, and a 12 h envelope reaches 52% at marginal grid-price parity. The marginal cost of decarbonization rises steeply beyond this point, in agreement with the findings of Jafari et al. [53] that storage-duration requirements increase nonlinearly once renewable penetration exceeds 50–60%. The practical implication for port operators is that an intermediate, storage-backed “smart-partial-renewable” target is more cost-effective than either a minimal-storage or a fully off-grid ambition.

The base-case storage is battery-dominant, 79 percent lithium-ion battery and 21 percent hydrogen. As Section 4.7 shows, this is not an interior cost optimum: with the battery share left unbounded the cost-optimal storage is essentially pure battery, because the battery’s high round-trip efficiency and fast response suit the predominantly diurnal mismatch of this summer-peaked load, and the 21 percent hydrogen is retained as a deliberate longer-duration reserve rather than on cost grounds. Treating the storage mix as a decision variable is nonetheless valuable precisely because it reveals this dominance rather than presupposing a mix; it also exposes a sizing subtlety, in that matching the hydrogen power components to the energy of the tank (Section 3.4) makes the hydrogen subsystem far more competitive than a naive percentile-based power sizing, which over-sizes the electrolyzer and fuel cell relative to a small tank and inflates the levelized cost, an effect corrected in the present model.

5.2. Comparison with Baseline Scenarios

Three baselines contextualize the performance. Relative to the auxiliary-engine scenario (428 tCO₂eq/yr for the at-berth phase), the optimized HRES-CI configuration reduces at-berth GHG emissions by 72% while eliminating the associated SO_x, NO_x, and particulate emissions that degrade air quality in port-adjacent communities [11,14]. Relative to grid-only CI (217 tCO₂eq/yr, 0.36 €/kWh), it reduces emissions by 45% and the LCOE by about 10% on a delivered-energy basis (21% when exported renewables are credited). Because a levelized cost is available only for the grid-connected baselines, the combined cost-and-emissions comparison is made against grid-only CI, which the HRES-CI configuration improves on both dimensions, whereas the auxiliary-engine comparison is on emissions and local air quality alone (72% lower GHG, plus elimination of the SO_x, NO_x and particulate emissions of at-berth combustion). The 45% reduction relative to grid-only CI is particularly significant in the Mediterranean context, where several national grids remain more carbon-intensive than the European average; the sensitivity analysis confirms that this environmental advantage is largest precisely where the local grid is most carbon-intensive, while the life-cycle emissions of PV (37.3 gCO₂/kWh) keep the investment environmentally favorable even against a substantially decarbonized grid.

5.3. The Role of Smart Sizing and Process-Oriented Energy Management

The results underscore that smart sizing, the joint optimization of renewable and storage capacities against a specific, high-resolution load profile, is decisive for the techno-economic viability of renewable-powered CI. A naive energy-matching rule would misjudge both the resource mix and the storage requirement, because it ignores the temporal coincidence between the summer PV peak and the summer CI peak and the role of storage in shifting that energy to the evening. By evaluating every candidate against the full 8760 h

simulation, the GA discovers the PV-plus-battery architecture and the storage envelope that balance the diurnal and seasonal patterns of generation and demand. This reinforces the conclusions of He et al. [44] on planning–operation co-optimization and aligns with the process-integration methodology of Beck et al. [54].

The EMS is equally critical. The deterministic priority order (renewables, battery, hydrogen, grid) ensures that storage is used in order of increasing marginal cost and decreasing efficiency, maximizing the value extracted from each unit of renewable generation, with the grid called upon only as a reliability backstop. The choice to keep the dispatch logic transparent and rule-based, rather than adopting model predictive control or reinforcement learning, is deliberate: in SMSP contexts operational simplicity and interpretability are valued over the marginal economic gain of more sophisticated controllers [63,73], consistent with the broader evidence from Jung and Yoon [79] and Jamal et al. [86] that well-designed rule-based strategies provide transparent and effective dispatch for loads of this character, under the flat-tariff, self-consumption-maximizing conditions assumed here; a formal comparison against predictive controllers under time-varying tariffs is left to future work (Section 5.5).

5.4. Scalability and Transferability

The framework is designed for replicability. Transferring it to another port requires only four routinely available local inputs: a year of hourly (or call-level) at-berth energy records, on-site or reanalysis solar and wind resource data, the retail electricity price, and the grid carbon factor. The cold-ironing demand model, the resource models, the optimizer and the controller are generic; only the vessel stay-duration distributions are re-parameterized, from local call statistics, after which the framework runs unchanged. Because the method discovers rather than presupposes the resource mix, the outcome adapts to the destination port's demand shape: the summer-peaked cruise port studied here draws the optimum toward photovoltaics, whereas a winter-baseload cargo or ferry port, whose demand aligns with the stronger winter wind resource, would shift it toward wind and, plausibly, toward longer-duration storage. The single most influential transferable driver is the local grid carbon factor, which governs the achievable emission reduction (30 to 49 percent across the range examined) while barely affecting the levelized cost, so the environmental value of the investment is greatest at ports served by the most carbon-intensive grids. The sensitivity analysis thus doubles as a decision-support tool, and a multi-port study across Mediterranean small and medium-sized ports with contrasting seasonality is the natural next step to map the port typologies for which renewable-powered cold ironing is most attractive.

5.5. Limitations and Future Research Directions

Several limitations should be acknowledged. First, the cold ironing demand model, although energy-conserving and physically constrained, remains a stochastic reconstruction calibrated on operational call records rather than on metered at-berth power or vessel-tracking logs; the model exposes an Automatic Identification System calibration hook for this purpose, and higher Monte Carlo counts and empirical duration calibration are recommended before site-specific investment decisions; moreover, the genetic algorithm was evaluated on the single fixed ensemble-mean profile, so load stochasticity was not propagated into the sizing. Second, the renewable resource data correspond to a single meteorological year, so inter-annual resource variability and climate trends are not captured; in addition, the anemometer height of the wind record was undocumented and was assumed to be 10 m, an assumption to which the wind capacity factor, and hence the marginal role of wind in the optimum, is sensitive; the normalized power curve of a multi-

megawatt reference turbine was moreover applied to the smaller turbine class considered here, so the 36.5 percent wind capacity factor should be read as an upper estimate for that class. Third, the full life-cycle costing reported in Section 4.7 relies on assumed O&M rates and a single mid-life replacement schedule; firm replacement timing, site-specific O&M contracts, and the battery-cost-decline trajectory materially affect the resulting LCOE and payback and warrant project-specific refinement. Fourth, the EMS is a deterministic rule-based strategy; a comparative assessment against model predictive control [80] or reinforcement-learning dispatch [77] would quantify the value of additional sophistication under time-varying tariffs. Fifth, the hydrogen subsystem uses efficiency-based electrolyzer and fuel cell representations; higher-fidelity electrochemical models would refine part-load behavior. Sixth, demand-side measures, berthing-schedule coordination or onboard load shifting, that could further flatten the CI peak are not considered, and their co-optimization with HRES sizing, building on the process-scheduling integration of Beck et al. [54], is a promising direction. Finally, a multi-port study spanning Mediterranean SMSPs with contrasting demand seasonality, including winter-baseload cargo and ferry ports for which wind is expected to play a larger role, would test the generalizability of the findings and map the port typologies for which renewable-powered CI is most attractive.

6. Conclusions

This study has presented an integrated smart-sizing and energy-management framework for grid-connected hybrid renewable energy systems supporting cold ironing at small and medium-sized ports of the Trans-European Transport Network. Using real operational data from a Mediterranean case-study port, the framework combines an enhanced, energy-conserving stochastic cold-ironing demand model, physically based photovoltaic and wind generation models, a hybrid battery–hydrogen storage architecture, a deterministic priority-ordered Energy Management System, and a genetic algorithm-based optimization that sizes the renewable and storage capacities jointly.

The principal conclusions are:

1. Renewable-powered cold ironing is competitive at the screening level and decarbonizes deeply, though its full life-cycle economics remain marginal at current battery costs. The base-case design (380 kilowatts of photovoltaics and a 2064 kilowatt-hour storage envelope split about four-fifths battery to one-fifth hydrogen) lowers the levelized cost of energy by roughly 10 percent on a delivered-energy basis and cuts greenhouse-gas emissions by 45 percent relative to grid-only cold ironing, and by 72 percent relative to auxiliary engines while removing local air pollutants. Adding operation, maintenance, and one mid-life battery replacement raises the levelized cost to about grid parity and lowers the internal rate of return to roughly 4 percent, so the case rests increasingly on the value of decarbonization and on projected battery-cost declines.
2. The optimal resource mix follows the demand shape. For the summer-peaked, cruise-driven demand of the case-study port, solar photovoltaics is the dominant cost-optimal resource because its output coincides with the demand, whereas the winter-biased wind resource is selected only in the storage–light configuration. The framework discovers rather than presupposes the mix and would favor wind at ports with winter-dominated baseload demand.
3. Storage, not renewable oversizing beyond demand, drives deep decarbonization. Holding the photovoltaic capacity fixed, added storage lifts the emission reduction from 15 to 45 percent, and an eight-to-twelve-hour storage envelope reaches 45 to 52 percent at or marginally above grid-price parity. A storage-backed, partial-renewable target is the cost-effective design point.

4. High-efficiency battery storage dominates the cost-optimal design for this diurnal load. When the storage split is left free, the cost-optimum is essentially pure battery; the 79-to-21 percent battery-to-hydrogen split of the base-case design (identical across all 30 robustness seeds, and within 0.27 percent of the global optimum verified by exhaustive enumeration and by an independent particle swarm optimizer) reflects a deliberately retained hydrogen reserve rather than a cost optimum. The value of treating the split as a decision variable is that the framework reveals this dominance rather than presupposing a mix; a hydrogen fraction is justified on cost grounds only where the cold-ironing mismatch is genuinely multi-day or seasonal.
5. The framework is scalable and replicable across the small and medium-sized ports of the Trans-European Transport Network. Its only port-specific inputs are the hourly demand, resource, and tariff data routinely available to operators, and the sensitivity analysis provides a ready decision-support tool for evaluating investments under different economic and grid-decarbonization trajectories.

For port operators and policymakers, the framework offers a quantitative, data-driven decision-support tool for renewable-powered cold-ironing investments, a need that grows more urgent as the 2030 shore-power compliance deadline approaches. Whether cold ironing delivers genuine decarbonization or merely shifts emissions from the quayside to the power plant will depend on how much local renewable energy is integrated; smart sizing and transparent energy management, as demonstrated here, are the enabling methodologies for the former outcome.

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Abbreviations

Abbreviation	Definition
AFIR	Alternative Fuels Infrastructure Regulation
AMP	Alternative Maritime Power
BESS	Battery Energy Storage System
CAPEX	Capital Expenditure
CI	Cold Ironing
CRF	Capital Recovery Factor
EII	Economic Index
EMS	Energy Management System
EnvII	Environmental Index
GA	Genetic Algorithm

GHG	Greenhouse Gas
H ₂ -ESS	Hydrogen Energy Storage System
HHV	Higher Heating Value
HRES	Hybrid Renewable Energy System
IMO	International Maritime Organization
IRR	Internal Rate of Return
LCOE	Levelized Cost of Energy
MPC	Model Predictive Control
NOCT	Nominal Operating Cell Temperature
NPC	Net Present Cost
nZEP	Nearly Zero Energy Port
PEM	Proton Exchange Membrane
PII	Political Index
PM	Particulate Matter
PSO	Particle Swarm Optimization
PV	Photovoltaic
ROI	Return on Investment
SII	Social Index
SMSP	Small and Medium-Sized Port
SSP	Shore-to-Ship Power
TEN-T	Trans-European Transport Network
TII	Technological Index

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