

A distributed system-of-systems architecture for cyber-physical coordination of maritime autonomous surface ships and smart ports

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Abstract

The increasing deployment of maritime autonomous surface ships (MASSs) and smart ports requires continuous cyber-physical coordination between autonomous vessels and port infrastructure. This paper develops a distributed system-of-systems (SoS) architecture integrating the hybrid digital twins HDTs of MASSs and smart ports for coordinated navigation, automated mooring, and energy management. The proposed approach combines a distributed linear time-varying model predictive control (LTV-MPC) algorithm with physics-informed neural networks (PINNs) for real-time approximation of shallow-water hydrodynamics and a decentralized alternating direction method of multipliers (ADMM) algorithm for privacy-preserving optimization of cold ironing and port microgrids. The developed models were evaluated using heterogeneous co-simulation under 5G URLLC communication conditions. The obtained results showed that coordinated vessel–port control eliminated unsafe berthing events in all simulated disturbance scenarios, reduced onboard maneuvering energy consumption by 42%, and shortened vessel stabilization time by 43%. The decentralized energy management algorithm increased renewable energy utilization to 84.2%, reduced peak grid demand from 18.5 MW to 9.1 MW, and decreased port operational expenditures by 45% without disclosing proprietary battery degradation information. The study also indicates that end-to-end communication latency below 10 ms is required to maintain stable cooperative control during automated mooring. These results support the feasibility of coordinated cyber-physical operation of autonomous vessels and smart ports based on distributed DTs.

Keywords

System-of-Systems, Digital twin, Model predictive control, Cold ironing, Distributed optimization, Physics-informed neural networks, 5G URLLC

1. Introduction

The evolution of maritime transport systems is characterized by a transition from isolated automation of individual shipboard systems toward integrated maritime logistics. At the current stage of cyber-physical systems (CPSS) development, MASSs are still predominantly regarded as independent agents whose interaction with shore infrastructure remains discrete and reactive, being largely limited to the automatic identification system (AIS) and conventional communication protocols. However, ensuring safe and economically efficient operation under intensive shipping conditions requires continuous cyber-physical synchronization between autonomous vessels and port infrastructure [1, 2]. The global maritime industry is undergoing a technological transformation driven by the parallel development of MASSs and smart ports [3]. The introduction of the IMO MASS Code in 2024 established the regulatory basis for highly autonomous commercial vessels employing artificial intelligence for navigation and machinery control [4, 6], while leading logistics hubs increasingly deploy 5G communications, the industrial internet of things (IIoT), and digital twin (DT) technologies for predictive infrastructure management [5].

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Nevertheless, the principal challenge is no longer the independent advancement of autonomous vessels or intelligent ports, but their seamless integration. Autonomous vessels cannot fully exploit services such as Just-in-Time Arrival and automated mooring within conventional port environments, whereas intelligent ports require continuous high-frequency information exchange with approaching vessels to realize their operational potential [3]. To address this challenge, this study considers a distributed cyber-physical architecture integrating the HDT of an autonomous vessel with the digital twin of a smart port. The integration of shipborne and shore DTs forms a SoSs capable of coordinating navigation, logistics, and port energy processes within a common cyber-physical environment. Such integration creates opportunities to improve maneuvering efficiency, reduce berth operation time, and support coordinated management of shore energy resources. In recent years, the integration of MASS and intelligent port infrastructure has attracted considerable attention from the international research community. Study [7] presents a comprehensive methodology for assessing the sustainability and environmental performance of port facilities using DT technology, whereas study [8] extends this concept by adapting digital twin methodologies developed for smart cities and supply-chain management to intelligent ports. However, both studies focus primarily on logistics synchronization and do not address high-frequency physical interaction between autonomous vessels and port infrastructure. The vessel–port interaction during automated berthing is systematically reviewed in [9], where existing control algorithms are classified and shown to remain predominantly vessel-centric, with the port represented mainly as a set of static constraints. Similarly, studies [10, 14] establish the foundations of remote engineering, predictive maintenance, and navigational safety for MASS, but continue to treat autonomous vessels as independent systems supervised by remote control centers rather than synchronized components of a distributed cyber-physical environment. Significant efforts have also been devoted to the decarbonization of maritime transport through shore power supply systems. The review presented in [12] identifies cold ironing as one of the principal technologies for zero-emission ports, whereas study [11] analyzes the challenges of integrating shore power into urban distribution networks. Practical optimization of renewable-energy-based port microgrids is investigated in [13]. Nevertheless, these studies generally assume deterministic vessel arrivals and centralized optimization without continuous bidirectional synchronization between onboard and shore energy systems. At the system level, study [15] identifies interoperability and standardized continuous data exchange as the principal barriers to large-scale MASS deployment. Consequently, despite substantial progress in autonomous navigation, intelligent ports, and port energy management, a unified framework for continuous cyber-physical synchronization between autonomous vessels and intelligent port automated management systems has not yet been established. Furthermore, existing cold ironing approaches remain predominantly centralized and require disclosure of commercially sensitive information, including onboard battery thermal degradation estimates (T_{FHT}), thereby limiting their practical implementation. Based on these research gaps, the objective of this study is to develop and mathematically formalize a distributed cyber-physical SoSs integrating the HDTs of autonomous vessels with intelligent port infrastructure. To achieve this objective, the study: formalizes a telecommunications model for continuous cyber-physical synchronization considering semantic interoperability and critical 5G communication delays; synthesizes a distributed linear time-varying model predictive control (LTV-MPC) algorithm using onboard PINNs; develops a decentralized optimization framework based on the alternating direction method of multipliers (ADMM) for port microgrids supporting cold ironing while preserving the confidentiality of battery thermal degradation estimates (T_{FHT}); verifies the proposed architecture through heterogeneous co-simulation and statistical robustness.

2. Information and telecommunication paradigm of the SoS in the “ship–port” system

The classical interaction between a ship and a port is characterized by discreteness and high data transmission latency. Within the SoS paradigm, this interaction is considered as a continuous

process of cyber-physical synchronization between two independent complex systems. To implement this synchronization safely, the critical constraint that must be formally defined is the communication delay (τ_d). For critical operations (e.g., mooring), this delay is defined by the following inequality:

$$\tau_d(t) = t_{proc} + \frac{V_{data}}{B_{channel}(t)} + t_{prop} \leq \tau_{crit}, \quad (1)$$

where t_{proc} is the processing time at edge-computing nodes; V_{data} is the data packet size; $B_{channel}(t)$ is the dynamic bandwidth of the hybrid communication channel (5G/VDES/LEO Satcom); t_{prop} is the signal propagation delay; τ_{crit} is the maximum permissible data transmission delay for the current technological operation. Satisfying such stringent information synchronization requirements is extremely difficult within conventional coastal communication infrastructures (e.g., 4G LTE or Wi-Fi 5). For the practical implementation of the proposed SoS paradigm, it is necessary to quantify the values of τ_{crit} across different interaction phases (Table 1).

Table 1

Telecommunication infrastructure requirements for the SoS framework at different stages of port arrival

Operational phase	Type of transmitted data	Required update rate	Maximum latency (τ_{crit})	Primary communication channel
Distant approach (>50 nautical miles)	JIT profiles, ETA, meteorological data, TFHT estimations	Once every 15 min	5000 ms	LEO Satcom (Starlink/OneWeb)
Anchorage / approach channel	Trajectories, VTS data, digital pilotage information	1 Hz	< 500 ms	VDES / 4G LTE
Berthing approach (maneuvering)	Vessel kinematics, tugboat status, depth information	10 Hz	< 50 ms	5G (port network)
Automated mooring	Port LiDAR data, mooring control commands	50–100 Hz	< 10 ms	5G URLLC / Wi-Fi 6 (LoS)

The priority of the network architecture shifts from bandwidth capacity to strict latency minimization as the system transitions to dynamic operations within the port water area (automated mooring). These threshold values are mathematically justified by the stability criteria of digital control systems. According to the classical theory of networked control systems (NCS) [16], the condition for preserving asymptotic stability in a delayed system is defined by the inequality:

$$\tau_d < \frac{\phi_m}{\omega_c},$$

where ϕ_m is the phase margin of the uncompensated system, and ω_c is the crossover frequency of the control loop. To analytically determine the critical delay τ_{crit} , it is necessary to distinguish between the slow kinematics of the vessel and the fast dynamics of the actuators. The critical control object during berthing is the rigid coupling between the vessel hull and the hydraulic actuators of the shore-based automated mooring system (AMS). To actively damp vessel micromotions and suppress destructive high-frequency hydraulic oscillations (actuator chattering), the internal force-control loop requires a bandwidth of at least 12.5 Hz. This determines the required crossover frequency of the cooperative closed-loop control system: $\omega_c = 2\pi f \approx 78.5$ rad/s. Assuming the minimum phase margin required to maintain asymptotic stability of the

hydraulic system is $\phi_m \approx \pi/4$ rad (45°), the maximum permissible network transport delay is obtained analytically as:

$$\tau_{crit} < \frac{\pi/4}{78.5} \approx 0.01 \text{ s}$$

Violation of this inequality introduces an uncompensated phase shift, inevitably leading to overshoot, loss of actuator stability, and a potential collision with the berth. The satisfaction of such stringent boundary conditions ($\tau_{crit} < 10$ ms) is possible exclusively through the deployment of dedicated private 5G port networks supporting ultra-reliable low-latency communication (URLLC). To synthesize the cooperative control algorithms (MPC and ADMM) within this established telecommunication framework, it is necessary to explicitly parameterize the phase spaces of the DTs whose data circulate within the SoS network.

$$x_{MASS} = [x, y, \psi, u, v, r, T_{FHT}^{(i)}, P_{load}, SOC]^T \in S_{MASS}, \quad (2)$$

where x, y, ψ, u, v, r are the kinematic parameters (position, heading, linear and angular velocities); $T_{FHT}^{(i)}$ is the predictive estimate of the Markov time to the limiting state of critical machinery; P_{load} is the forecast power demand; SOC is the current state of charge of the onboard batteries. Accordingly, the state space of the intelligent port DT is described by the vector:

$$x_{PORT} = [traffic, depth, wind, grid_state, price]^T \in S_{PORT}, \quad (3)$$

where *traffic* is the local shipping traffic matrix; *depth* is the dynamic depth map (taking into account tidal variations and subsidence effects); *wind* is the vector of hydrometeorological disturbances (τ_{env}^{port}); *grid_state* is the energy balance of the port microgrid (including renewable energy generation); *price* is the dynamic vector of shadow electricity tariffs. The continuous and guaranteed synchronisation of these variables (with a delay of $\tau_d < 10$ ms) enables the transition to the solution of specific cyber-physical control tasks. The structural diagram of the resulting macroarchitecture Σ_{SoS} is presented in Figure 1.

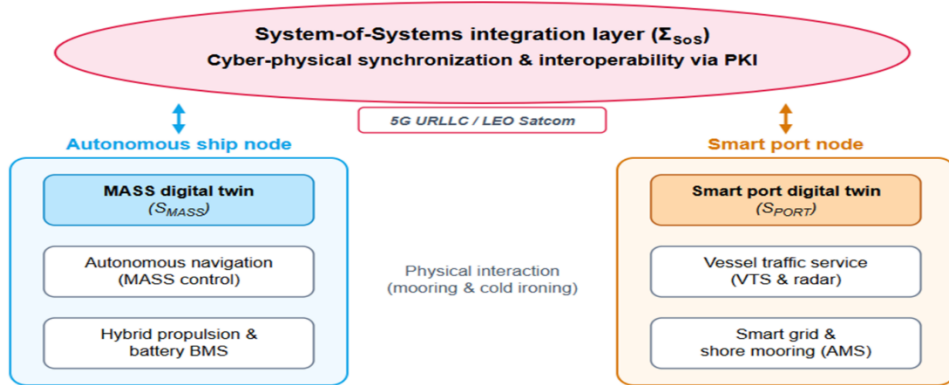


Figure 1: Macroarchitecture of the SoS metasystem: physical, telecommunication, and cyber-physical integration of the autonomous vessel and the intelligent port.

The SoS macroarchitecture (Fig. 1) establishes the orthogonality of physical and cognitive flows. The physical layer (mooring, energy transfer) remains constrained by high inertia and nonlinear hydrodynamics, whereas the predictive integration layer (Σ_{SoS}) enables the (DTs to functionally "outrun" real time. Using predictive vectors from the vessel's DT, the port proactively prepares its microgrid and AMS prior to actual physical contact. Crucially, a public key infrastructure (PKI) logically isolates critical onboard safety loops (navigation, BMS) from the external optimizer. Consequently, even during a successful 5G network breach, low-level actuator control remains secure; the local DTs immediately switch to a safe degradation mode, preserving the fundamental autonomy of each agent.

3. CPC of automatic mooring processes based on hybrid models

Automatic mooring requires centimeter-level accuracy under intensive stochastic disturbances (wind, shallow-water currents). Within the SoS paradigm, control shifts from an isolated onboard system to coordinated operation, where the port DT manages shore-based AMSs and provides high-resolution local data. The vector-matrix equation of motion is:

$$M(\eta)\dot{v} + C(v)v + D(v)v = \tau_{ctrl} + \tau_{env}^{port} + \tau_{AMS}, \quad (4)$$

where $\eta = [x, y, \psi]^T$ is the position and heading vector in the local berth coordinate system; $v_{ctrl} = [u, v, r]^T$ is the velocity vector; M, C, D are the inertia, Coriolis force, and damping matrices (strongly nonlinear in shallow water and corrected by PINN models); τ_{ctrl} is the control vector of the vessel's propulsion units (azipods and thrusters); τ_{env}^{port} is the environmental disturbance vector transmitted from the port digital twin (high-precision local data); τ_{AMS} is the attraction force vector generated by the shore-based automatic mooring systems.

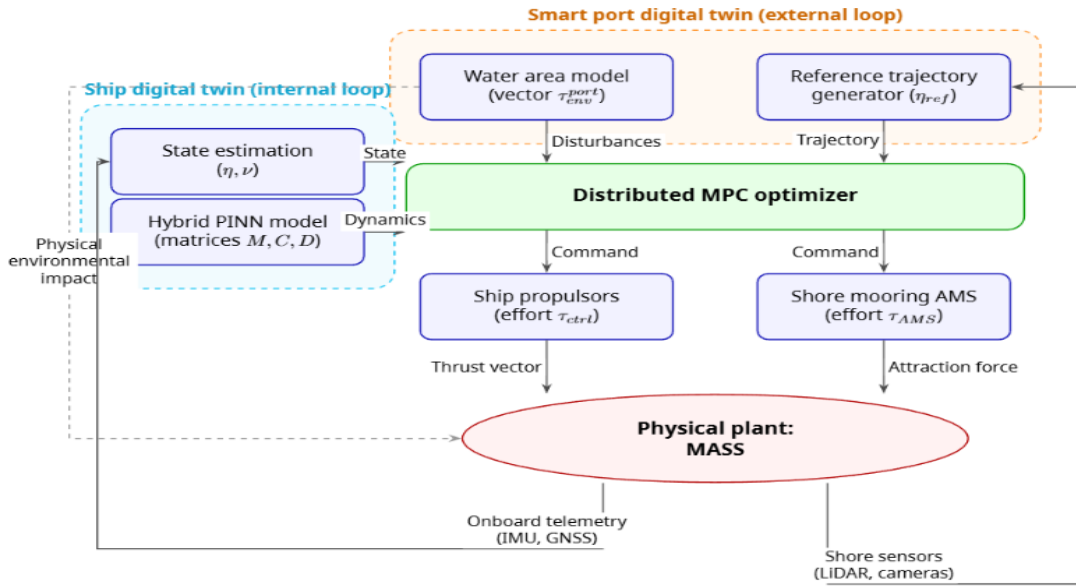


Figure 2: Structural diagram of cooperative MPC-based automatic mooring control within the SoS paradigm.

In shallow water ($T/h \rightarrow 1$), hydrodynamic matrices become highly nonlinear. Rather than relying on static coefficients, the SoS architecture dynamically approximates these parameters using onboard PINNs. Trained offline using CFD datasets and validated against full-scale trials, the PINN surrogate model explicitly incorporates Navier-Stokes differential residuals into its loss function. This guarantees physical consistency, such as the positive definiteness of the damping matrix, enabling the MPC optimizer to compute highly accurate M, C, D matrices within milliseconds, avoiding the "black-box" uncertainty of conventional networks. The distributed architecture (Fig. 2) resolves the curse of dimensionality by decoupling the outer port-side loop (1 Hz) from the inner vessel-side loop (10-50 Hz).

The port DT updates macro-parameters, while the vessel DT compensates for high-frequency disturbances. By delegating nonlinear hydrodynamic computations to the hybrid PINN model, we minimize the computational burden on the central MPC module, ensuring the control solution is computed within the critical latency threshold ($\tau_{crit} < 10$ ms). The distributed MPC optimizer minimizes deviations from the reference berthing trajectory (η_{ref}) while constraining control aggressiveness (τ_{ctrl}, τ_{AMS}):

$$\sum_{k=1}^{N_p} \|\eta(t+k|t) - \eta_{ref}(t+k)\|_Q^2 + \sum_{k=0}^{N_u-1} (\|\Delta\tau_{ctrl}(t+k)\|_{R_1}^2 + \|\Delta\tau_{AMS}(t+k)\|_{R_2}^2), \quad (5)$$

subject to the physical and spatial constraints:

$$\tau_{ctrl}^{min} \leq \tau_{ctrl} \leq \tau_{ctrl}^{max}; \quad 0 \leq \tau_{AMS} \leq \tau_{AMS}^{max}; \quad v_{impact} \leq v_{safe}; \quad N_p \cdot \eta(t+k|t) \leq b_p$$

where N_p, N_u are the prediction and control horizons in discrete steps k ; η_{ref} is the prescribed (reference) approach trajectory to the berth; Q, R_1, R_2 are the positive-definite diagonal weighting matrices defining the balance between positioning accuracy and the energy expenditure associated with aggressive control actions; $\Delta\tau_{ctrl}, \Delta\tau_{AMS}$ are the increments of the control actions at the current step, the limitation of which within the objective function ensures smooth operation of the mechanisms; v_{safe} is the maximum permissible closing velocity (landing velocity), limiting the kinetic energy of fender contact and ensured through the coordinated operation of the vessel propulsion system and the shore-based vacuum grippers; N_p and b_p are the matrices and vectors defining the safe navigable corridor polytope generated by the port DT on the basis of LiDAR data. To balance navigational safety and computational efficiency, the horizons are established at $N_p = 200$ (providing a 20-second prediction window critically necessary to compensate for the 65,000-ton hull inertia) and $N_u = 50$. The weighting matrices strictly prioritize navigational safety over energy consumption. The state-error matrix $Q = diag(10^4, 10^4, 10^5)$ heavily penalizes spatial deviations. The control cost matrices are configured asymmetrically: $R_1 = diag(10^{-1}, 10^{-1}, 10^{-1})$ for vessel azipods and $R_2 = diag(10^{-3}, 10^{-3}, 10^{-3})$ for shore-based AMS. The condition $R_2 \ll R_1$ algorithmically compels the optimizer to transfer the physical stabilization effort to the port network, preserving the onboard batteries. High weights in R_2 simultaneously smooth control gradients ($\Delta\tau$) to prevent destructive actuator chattering. To guarantee solvability within the telecommunication threshold ($\tau_{crit} < 10$ ms), the highly nonlinear hydrodynamic matrices $M(t), C(t), D(t)$ generated by the PINN model are treated as quasi-stationary over the prediction horizon N_p . This implements a linear time-varying (LTV-MPC) paradigm, effectively reducing the complex optimization to a standard quadratic programming (QP) formulation.

4. Energy integration: system-level optimization of microgrids and cold ironing technologies

The implementation of the Zero-Emission Port concept is impossible without the application of onshore power supply (OPS) technology, also known as cold ironing. The integration of MASS into the port Smart Grid requires a transition from static shore-power connection to dynamic energy-consumption optimization based on digital twin predictions.

4.1. Formation of the MASS DT load profile

Based on cargo loading/unloading schedules and battery charging requirements (for hybrid or fully electric vessels), the vessel DT generates a predictive power-demand profile $P_{MASS}^{pred}(t)$ for the entire berthing interval $[t_{arr}, t_{dep}]$.

4.2. Shore-side power system balancing

The digital twin of the smart port treats berthed vessels as active nodes (prosumers) within the local microgrid. The port power-balance equation at time t is expressed as:

$$P_{grid}(t) + P_{RES}(t) + P_{ESS_dis}(t) = P_{base_port}(t) + \sum_{i=1}^{N_{MASS}} P_{MASS_i} + P_{ESS_ch}(t), \quad (6)$$

where P_{grid} is the power imported from the main electrical grid; P_{RES} is the power generated from renewable energy sources (solar and wind installations located within the port area); P_{ESS_dis} ,

$P_{ESS_{ch}}$ are the discharge and charge power of shore-side energy storage systems; P_{base_port} is the baseline electrical load of the port (cranes, terminal facilities, and auxiliary infrastructure). The physical topology of energy flows within the ship–port system, described by this power-balance equation, is illustrated in Figure 3.

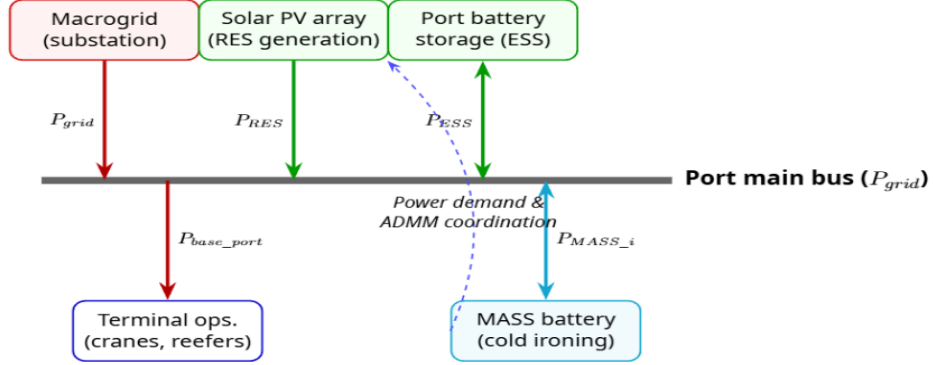


Figure 3: Structural diagram of power flow distribution in a smart port microgrid with integrated autonomous vessels (cold ironing)

In a conventional uncoordinated configuration, stochastic vessel connections (P_{MASS_i}) act as passive loads, generating transient spikes on the main bus and forcing expensive electricity imports from the utility grid (P_{grid}). The proposed SoS architecture introduces a cyber-physical coordination layer, transforming the MASS into an active prosumer. Maintaining power balance and minimizing port OPEX requires strict algorithmic synchronization of vessel charging profiles with renewable generation peaks (P_{RES}) and shore-based storage cycles (P_{ESS}). This dynamic coordination dictates the objective function for the microgrid economic dispatch.

4.3. Economic dispatch objective function

The objective of the port DT is to minimize total operational expenditures (OPEX) and carbon emissions while satisfying the energy requirements of the fleet. The objective function J_{energy} is formulated as:

$$\min J_{energy} = \int_{t_{arr}}^{t_{dep}} [C_{grid}(t)P_{grid}(t) + \lambda_{CO2} \cdot E_{CO2}(P_{grid}) + \sum_{i=1}^{N_{MASS}} C_{deg_i}(P_{MASS_i})] dt, \quad (7)$$

where $C_{grid}(t)$ is the dynamic utility electricity tariff (time-of-use tariff); λ_{CO2} is the cost of greenhouse gas emission allowances (carbon tax); E_{CO2} is the emission function associated with electricity generation; C_{deg_i} is the cost function representing the thermal degradation of the battery for vessel i , quantified via predictive TFHT estimation algorithms. Minimization of the objective function is performed under strict physical and operational constraints of the microgrid. Main transformer capacity constraint (grid connection point):

$$P_{grid}(t) \leq P_{max}^{transformer}$$

SOC constraints for shore-side and onboard energy storage systems:

$$\begin{aligned} C_{min} &\leq SOC(t) \leq SOC_{max}, \\ SOC(t+1) &= SOC(t) + \frac{\eta_{ch} \cdot P_{ch}(t) - P_{dis}/\eta_{dis}}{E_{capacity}}, \end{aligned} \quad (8)$$

where η_{ch} , η_{dis} are the denote charging and discharging efficiencies; $E_{capacity}$ is the nominal battery energy capacity. Nonlinear power-flow constraints, which regulate both active and reactive power balance within network nodes to prevent critical voltage sag events during peak cold ironing demand periods. In terms of variational optimization, the gradient of the objective function J_{energy} drives the system toward operating conditions where $C_{grid}(t) \rightarrow \min$, and $P_{RES}(t) \rightarrow$

max. To identify this optimum in a decentralized manner under information asymmetry (where vessel owners must preserve the confidentiality of battery condition information), the alternating direction method of multipliers (ADMM) is employed. The distributed ADMM architecture (Fig. 4) resolves the fundamental conflict between optimal microgrid dispatch and commercial data privacy.

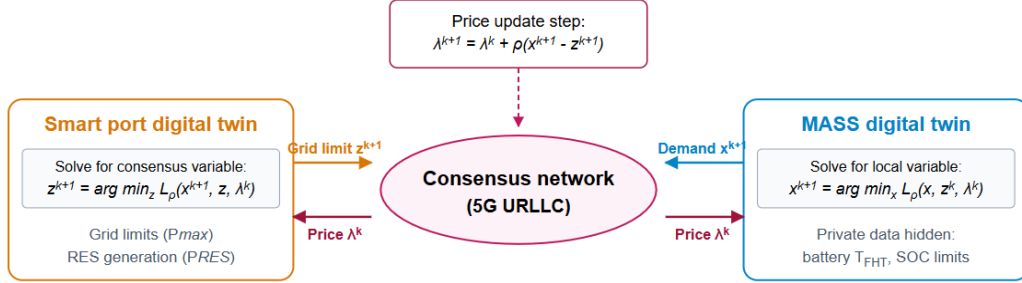


Figure 4: ADMM-based decentralized optimization architecture: system coordination of independent agents without disclosure of proprietary energy storage parameters (T_{FHT}).

Unlike traditional centralized dispatching that aggregates all local constraints, a major barrier to Cold Ironing, the ship and port DTs minimize their local objective functions independently. The 5G URLLC network transmits only low-dimensional vectors: requested/allocated power (x, z) and shadow prices (λ). This zero-knowledge topology guarantees asymptotic convergence to the global economic optimum (J_{energy}) without ever disclosing proprietary parameters of independent agents. Mathematically, the iterative process of decentralized ADMM optimization is based on minimizing the augmented Lagrangian function and is described by the following system of recursive equations:

$$x^{k+1} = \arg \min_x L_\rho(x, z^k, \lambda^k), \quad z^{k+1} = \arg \min_z L_\rho(x^{k+1}, z, \lambda^k), \quad \lambda^{k+1} = \lambda^k + \rho \cdot (x^{k+1} - z^{k+1})$$

where k is the iteration number of the data exchange process over the 5G network; $x \in X_{safe}$ is the vector of local optimization variables on the vessel digital twin side (formation of the requested power profile P_{MASS}^{pred} considering the degradation of the vessel's own batteries); $z \in Z_{grid}$ is the vector of consensus (global) variables on the port digital twin side (allocation of the available microgrid power taking into account generation capacity limits Z_{grid}); λ is the dual variables (vector of shadow electricity prices); $\rho > 0$ is the quadratic penalty parameter ensuring asymptotic convergence of the algorithm. Incorporating the nonlinear battery thermal degradation model renders the vessel's local objective function non-convex. Because classical ADMM guarantees convergence only for convex optimization problems, a sequential convex programming (SCP) method is integrated into the vessel's digital twin solver. By approximating the nonlinear degradation function with its convex majorant at each communication iteration, the distributed algorithm mathematically guarantees convergence to a safe local optimum (KKT point). This strictly satisfies the physical constraints of both the microgrid and the battery systems while maintaining the zero-knowledge privacy topology.

5. Verification of coordinated cyber-physical interaction algorithms using co-simulation

To validate the adequacy of the developed mathematical models and evaluate the effectiveness of the proposed SoSs architecture, a co-simulation study was conducted. The simulation environment combined two independent computational cores emulating the operation of heterogeneous digital twins: the dynamics of the MASS were modeled in MATLAB/Simulink (with integration of PINN modules implemented in Python/TensorFlow), while the electrical processes of the port microgrid were simulated in the specialized software package DlgSILENT PowerFactory. Data exchange

between the simulation cores was performed through the data distribution service (DDS) protocol, emulating a dedicated 5G port network with controlled packet latency. The architecture of the developed co-simulation testbed (Fig. 5) addresses the fundamental asynchrony between continuous-time hydrodynamic ODE solvers in MATLAB and quasi-steady-state electrical computations in PowerFactory.

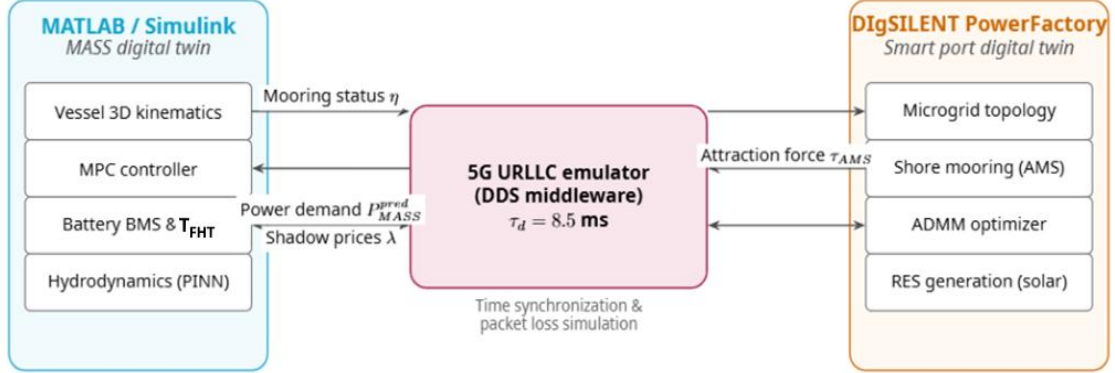


Figure 5: Architecture of the hardware-software co-simulation platform for heterogeneous DTs.

To ensure numerical stability, integration utilizes the functional mock-up interface (FMI) standard, with the DDS middleware acting as the Co-Simulation Master to enforce deterministic state-vector exchange at predefined rendezvous points. Zero-order hold (ZOH) extrapolators within each DT compensate for emulated 5G transmission delays (8.5 ms) and packet losses, preventing algebraic loops and guaranteeing solver stability. By embracing edge computing, computationally intensive tasks (PINN tensor operations and nonlinear power-flow calculations) are executed locally. Only compressed macro-parameters (λ , η , τ_{AMS} , (P_{MASS}^{pred})) traverse the 5G URLLC channel, ensuring latency remains within the 8.5 ms critical threshold even under peak network loads. Furthermore, this topology physically enforces the zero-knowledge privacy, as the port optimizer interacts with the vessel BMS solely via price vectors (λ) without accessing proprietary T_{FHT} data. Practical verification of this architecture was conducted using a Panamax-class autonomous container vessel baseline scenario. The key parameters of the simulation environment are summarized in Table 2.

Table 2

Parameters of the Σ SoS co-simulation environment

Model parameter	Value	Justification / Source
MASS displacement	65,000 t	Typical Panamax-class container vessel
Onboard battery capacity	8.5 MWh	Hybrid propulsion system
Shore-side AMS capacity	4×400 kN	Cavotec MoorMaster vacuum mooring units
Base port load	2.5 – 3.0 MW	Operation of container cranes and terminal infrastructure
Peak renewable generation	5.0 MW	Rooftop solar installations on warehouse facilities
Emulated communication delay τ_d	8.5 ms	5G URLLC latency including jitter
MPC prediction horizon (Np)	20 s	Sampling interval of 0.1 s

The simulation scenario covered two operational phases: final approach and mooring under stochastic crosswind disturbances of up to 15 m/s; a 24-hour port stay with connection to the microgrid under the cold ironing operating mode.

5.1. Results of automatic mooring simulation

To evaluate the robustness of the developed MPC controller under environmental uncertainty, 50 extreme worst-case scenarios were simulated using a directed Monte Carlo sampling technique. These scenarios encapsulated peak wind-wave disturbances (15 m/s crosswinds) and dynamic shallow-water squat effects. The statistical sufficiency of the sample was rigorously validated via non-parametric bootstrapping ($B = 10,000$), confirming that the 95% confidence interval of the expected positioning error remains strictly within the safe navigation polytope ($H_p \cdot \eta \leq b_p$). A comparison was performed between isolated control (vessel propulsion only) and coordinated SoS control (vessel + shore-based AMS). The summarized results are presented in Table 3.

Table 3.

Comparative results of mooring simulations (50 monte carlo runs)

Evaluated parameter	Isolated control (vessel only)	Coordinated control (SoS: vessel + AMS)	Improvement
Maximum impact velocity (v_{impact})	Exceeds v_{safe} in 12% of cases	$v_{\text{impact}} < v_{\text{safe}}$ in all 50 runs	Safety guarantee
Onboard energy consumption during maneuver	142.5 kWh	82.6 kWh	42% reduction
Portion of force transferred ashore (τ_{AMS})	0% (system not engaged)	42% (distributed load sharing)	Reduced azipod wear
Vessel stabilization time at berth	14.5 min	8.2 min	43% reduction

Results in Table 3 confirm the mathematical hypothesis: the use of a hydrodynamic damping matrix dynamically corrected by a PINN model, combined with shore-based mooring mechanisms, not only prevents azipod thrust oscillations but also improves maneuvering safety. Delegating 42% of the physical control effort to external mooring systems resulted in substantial savings of onboard energy resources required during the maneuvering phase. The probability density functions (PDFs) of impact velocity from the 50 Monte Carlo runs (Fig. 6) demonstrate that isolated control cannot adequately compensate for vessel inertia under peak disturbances.

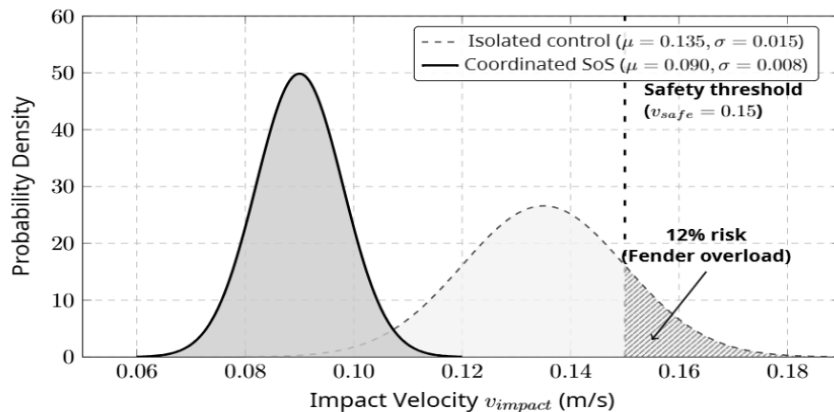


Figure 6: Probability density function (PDF) curves of the approach velocity (v_{impact}) at physical contact with the berth, approximated from the results of 50 Monte Carlo simulation runs.

This results in a pronounced right-hand tail exceeding the critical threshold ($v_{safe} = 0.15$ m/s), creating a 12% risk of infrastructure damage. Conversely, the coordinated SoS controller shifts the operation into a safe region (median 0.09 m/s) and drastically narrows the kinematic variance (95% CI: 0.074 to 0.106 m/s). A Fisher's F-test comparing the sample variances ($F(49, 49) = 6.45$, $p = 1.2 \times 10^{-5}$) rigorously rejects homoscedasticity. This statistically confirms that the cooperative MPC not only reduces the expected positioning error but virtually eliminates stochastic tail risks, ensuring deterministic safety during automated berthing.

5.2. Results of decentralized energy optimization

During the berth phase (cold ironing), the capability of the distributed ADMM algorithm to balance the port microgrid without direct access to the internal battery parameters of the vessel was evaluated. Based on the co-simulation setup and DDS-synchronization, the convergence dynamics of the objective function J_{energy} showed that the algorithmic residual error decreases below the specified tolerance threshold $\epsilon = 10^{-4}$ after exactly 14 iterations. Taking into account the established 5G URLLC latency (8.5 ms), the complete global optimization cycle at each 15-minute dispatch interval required less than 0.2 seconds of real time. The successful execution of decentralized economic dispatch is graphically illustrated in Figure 7. Analysis of the daily load profiles demonstrates that the implementation of coordinated control based on the SoS macro-architecture initiates two interrelated physical and economic processes: peak shaving and load shifting. The solution of the distributed optimization problem mathematically determines the transfer of the primary phase of vessel energy consumption to daytime hours, strictly synchronizing it with the bell-shaped generation curve of the local photovoltaic systems $P_{RES}(t)$.

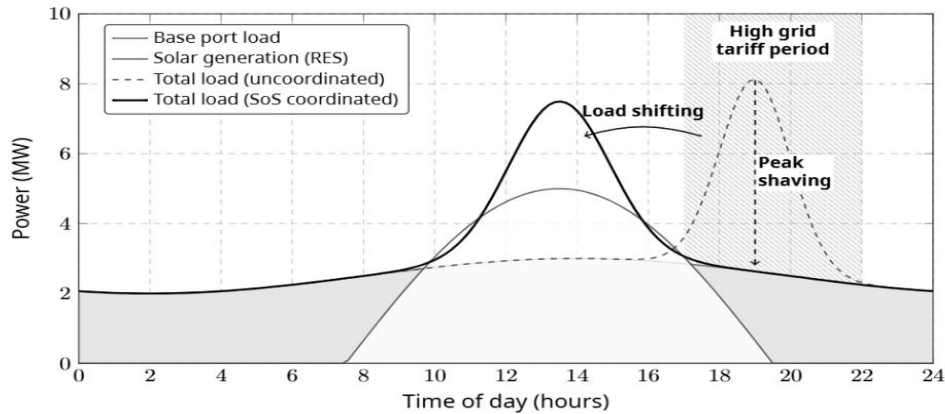


Figure 7: Dynamic balancing of the port microgrid using cognitive synchronization algorithms.

To objectively quantify the advantages of the proposed SoS macro-architecture, a comprehensive comparative analysis of various power supply and integration strategies was conducted based on the co-simulation results. Table 4 consolidates the performance metrics, contrasting conventional operational modes with the proposed cyber-physical synchronization. Analysis of the consolidated data mathematically demonstrates the superiority of the proposed macro-system architecture. In the conventional non-optimized scenario (plug-and-charge), the mismatch between consumption peaks compels the port to import electricity, resulting in a critical peak demand of 18.5 MW, while renewable energy utilization reaches only 31.4%. The implementation of the decentralized ADMM algorithm achieves a twofold reduction in peak demand (9.1 MW) and maximizes the share of "green" energy (84.2%). Ultimately, the proposed ADMM-based coordination reduces the total operational expenditures (OPEX) of the microgrid by 45.0% relative to the baseline uncoordinated cold ironing scenario, while strictly satisfying the physical limitations of shipowner battery systems. Thus, the hardware–software co-simulation environment, integrating nonlinear vessel maneuvering hydrodynamics and transient electrical processes of the port microgrid, empirically

verified the functionality, asymptotic convergence, and robustness of the proposed SoS macro-architecture.

Table 4

Comprehensive efficiency analysis of power supply and integration strategies

Power supply scenario	Integration & control method	Peak load (MW)	gridLocal utilization	RES Relative OPEX reduction compared to baseline
Isolated operation	None (onboard diesel generators only)	0.0	0.0%	Baseline
Standard cold ironing	Uncoordinated (plug-and-charge)	18.5	31.4%	Baseline OPEX (reference)
Centralized peak shaving	Heuristic (rule-based)	14.2	56.8%	18.5%
Proposed SoS architecture	Cooperative cyber-physical (ADMM)	9.1	84.2%	45.0%

6. Discussion

Contextualizing the proposed System-of-Systems architecture requires a comparison with current approaches to MASSs and smart port integration [17, 18]. Berthing control and physical integration. In contemporary studies, MASS berthing control problems are traditionally addressed in isolation. For example, [19] proposed a safety-certified MPC controller for autonomous vessel berthing. While their algorithm demonstrated high navigational accuracy, all compensation for physical forces relied exclusively on onboard propulsion systems, which inevitably increases energy consumption. The SoS framework proposed here circumvents this issue by shifting the physical control effort to shore-based automated systems, thereby reducing onboard energy consumption and actuator wear compared to vessel-centric solutions. Application of DTs. The importance of cyber-physical replicas is well-recognized; for instance, [22] established the foundations of a digital twin for the research vessel GUNNERUS, while [26] developed a digital twin tailored for port logistics. The present work conceptually bridges these two advanced domains. However, unlike studies focusing on independent twin deployment [22, 26], this research substantiates a co-simulation architecture where computationally intensive tasks are distributed across a heterogeneous environment, utilizing the DDS protocol as a practical time arbitrator. Decentralized energy optimization of microgrids. The application of the ADMM algorithm to port energy management was previously investigated by [20] for the allocation of electric vessels. Parallely, [23] demonstrated the viability of data-driven forecasting in cold ironing systems, and multimode maritime power networks were examined in recent reviews [24, 27]. Building upon these foundations, the present study introduces an essential operational condition: data confidentiality. Where our approach diverges is in the ADMM topology, which ensures the mathematical privacy of proprietary onboard parameters (such as T_{FHT}) without degrading the efficiency of microgrid dispatch. This addresses one of the primary commercial barriers to wider Cold Ironing adoption. Telecommunication constraints. Previous works [21] and 5G Multi-Hop experiments [25] have justified the use of 5G in maritime environments, typically reporting latencies of 15 – 20 ms for remote-monitoring applications. However, the theoretical and simulation findings in this study indicate that such latencies are insufficient for a closed-loop cooperative berthing system. The identified limit of $\tau_{crit} < 10$ ms aligns closely with 3GPP release 17 specifications [28] for industrial control, highlighting the practical necessity of deploying private URLLC networks specifically within smart port waters. Architecture scalability and multi-

agent conflict resolution. Although the co-simulation verified the results for a single vessel, real-world hubs serve dozens of MASS units simultaneously. The scalability of the proposed architecture rests on two mathematical foundations. First, the computational complexity of the ADMM method grows linearly, $O(N)$, because each vessel DT solves its local quadratic programming problem independently and in parallel. Resource conflicts are resolved through a consensus mechanism via the shadow price λ , requiring only lightweight vector aggregation from the central port node. Second, the telecommunication bottleneck is mitigated at the physical 5G layer via network slicing. Allocating dedicated physical resource blocks (PRBs) to berthing-control loops within the URLLC slice ensures deterministic latency, largely independent of the broader terminal traffic. Resilience and future directions. While the current study validates the SoS architecture under severe environmental disturbances and microgrid load variations, extending this framework to encompass systemic anomalies represents a critical direction for future research. Conceptually, the proposed architecture accommodates graceful degradation protocols (e.g., safe control transfer during 5G communication loss or AMS actuator failures) and zero-trust cybersecurity measures, such as L1-based state estimators against false data injection attacks (FDIA). Future empirical studies will focus on simulating these extreme edge cases to explicitly validate the system's cyber-resilience and hardware fault tolerance. Ultimately, evaluating these factors side-by-side illustrates the practical advantages of a synchronized SoS architecture over conventional isolated operations, particularly regarding maneuverability, energy distribution, and adherence to safety margins.

7. Conclusions

This study presented and validated a comprehensive SoS macro-architecture, overcoming the limitations of isolated MASS operations by continuously integrating them with smart port infrastructure. By establishing a unified cyber-physical synchronization loop, the research mathematically formalized and empirically proved the feasibility of shifting from reactive vessel-centric navigation to cooperative, predictive interactions. The effectiveness of the proposed algorithms was confirmed through rigorous hardware-software co-simulation. The distributed LTV-MPC controller, utilizing hybrid PINN models for real-time approximation of highly nonlinear shallow-water hydrodynamics, successfully delegated the physical stabilization effort to shore-based automated mooring systems (AMS). This cooperative approach deterministically eliminated the risk of infrastructure collision under severe disturbances (15 m/s crosswinds) and reduced onboard energy consumption during the maneuvering phase by 42%. In parallel, the decentralized ADMM optimization framework demonstrated its capability to globally balance port microgrid power flows, achieving 84.2% renewable energy utilization and a 45.0% reduction in total operational expenditures (OPEX). A critical scientific contribution of this architecture is its resolution of commercial data privacy barriers. The zero-knowledge topology of the ADMM algorithm mathematically guarantees the confidentiality of proprietary shipowner data, specifically, the predictive TFHT estimates of battery degradation, while still achieving the global economic optimum. Furthermore, the analytical derivation of the $\tau_{crit} < 10$ ms latency limit, based on networked control systems (NCS) theory, firmly substantiates the practical necessity of deploying dedicated 5G URLLC networks in port waters to prevent destructive actuator self-oscillations. Despite the highly promising results, the current study is primarily bounded by nominal operating conditions and extreme environmental disturbances. A vital direction for future research lies in evaluating the architecture's cyber-resilience and hardware fault tolerance. Future studies will focus on implementing and testing graceful degradation protocols under systemic anomalies, such as 5G communication blackouts or AMS actuator failures. Additionally, integrating robust L1-based state estimators within a Zero Trust Architecture to counter false data injection attacks (FDIA), alongside expanding the co-simulation environment to evaluate multi-agent conflict resolution in high-traffic hubs, represents the next critical step toward the large-scale commercial deployment of the SoS paradigm.

Declaration on Generative AI

In preparing this article, the authors used artificial intelligence tools (ChatGPT, Gemini) to refine the text, check grammar, translate the text and prepare illustrations. All sections prepared with the aid of AI were thoroughly checked, verified and edited by the authors to ensure academic accuracy. The research methodology, analytical results and conclusions presented in this paper are the result of the authors' original intellectual work. The authors accept full responsibility for the content and accuracy of the article.

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