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Energy–Information–Decision Coupling Optimization for Cooperative Operations of Heterogeneous Maritime Unmanned Systems

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Highlights

What are the main findings?

- A novel Energy–Information–Decision (EID) coupled optimization framework is established, which systematically models the intrinsic interdependencies between platform endurance, communication quality, and collaborative task scheduling for USV–UAV systems.
- A bi-level optimization algorithm integrating heuristic search with Multi-Agent Reinforcement Learning (MARL) achieves superior coordination; results demonstrate a task completion rate exceeding 93% and a significant reduction in both total energy consumption and replenishment waiting latency.

What are the implications of the main findings?

- The closed-loop adaptive mechanism successfully addresses critical endurance and communication bottlenecks, enabling heterogeneous unmanned systems to execute long-duration, large-scale missions in complex maritime environments with high reliability.
- This study demonstrates the practical value of integrated EID modeling in enhancing the autonomous decision making and robustness of marine systems, providing a solid technical foundation for future maritime surveillance and emergency response operations.

Abstract

With the growing applications of maritime unmanned systems in environmental monitoring, ocean patrol, and emergency response, achieving efficient multi-platform cooperation in complex and dynamic marine environments remains a critical challenge. Unmanned Aerial Vehicles (UAVs) provide flexible and high-coverage sensing capabilities but are constrained by limited energy capacity, whereas Unmanned Surface Vehicles (USVs) offer long endurance and can serve as mobile platforms and energy supply nodes. Existing studies mostly focus on single-factor optimization, lacking a systematic analysis of the coupled relationships among energy, information (communication and positioning), and task decision making. To address this problem, this paper proposes an Energy–Information–Decision Coupling Optimization Method for Cooperative Maritime Unmanned Systems. A unified coupling model is established to integrate task completion, energy consumption, communication delay, and replenishment scheduling into a multi-objective optimization



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framework. A bi-level optimization algorithm is designed: the upper layer optimizes USV trajectories and energy supply strategies, while the lower layer optimizes UAV path planning and task allocation. A closed-loop adaptive mechanism is incorporated to achieve optimal cooperation under dynamic tasks and energy constraints. Extensive simulations combined with real-world experimental data are conducted to evaluate the method in terms of mission efficiency, energy balance, communication latency, and system robustness, with ablation studies quantifying the contribution of the coupling module. Results demonstrate that the proposed method significantly outperforms non-coupled or single-factor optimization strategies across multiple performance metrics: it achieves a task completion rate exceeding 93%, reduces total energy consumption by approximately 6% and replenishes waiting latency by over 28% compared with the decoupled baseline method. This effectively enhances the cooperative efficiency and robustness of maritime unmanned systems, and provides theoretical and methodological guidance for large-scale, complex ocean missions.

Keywords: maritime unmanned systems; UAV–USV cooperation; energy–information–decision coupling; multi-objective optimization; closed-loop coordination

1. Introduction

With the rapid advancement of unmanned system technologies, maritime unmanned systems have been extensively deployed in fields such as environmental monitoring, maritime surveillance, marine resource exploration, and emergency response [1–3]. Compared to single-platform operational modes, heterogeneous collaborative systems comprising USVs and UAVs offer significant advantages in task coverage, mission efficiency, and system robustness. Specifically, UAVs possess high maneuverability, broad fields of view, and rapid deployment capabilities, making them ideal for large-scale aerial perception and target identification [4,5]. In contrast, USVs provide long endurance, high payload capacity, and stable operation, serving as surface observation platforms, communication relay nodes, and energy-supply carriers [6,7]. The complementary strengths of USVs and UAVs establish them as an ideal collaborative architecture for executing large-scale, long-duration maritime missions. Meanwhile, recent studies have focused on key technologies for air–water collaborative observation systems, providing technical support for the practical deployment of USV–UAV collaborative missions [6].

Extensive research has been conducted on USV–UAV heterogeneous collaborative systems, focusing on collaborative task allocation, path planning, cooperative control, and information perception. Regarding multi-platform maritime observation, Yang et al. proposed an optimization framework for joint path planning and task scheduling, enhancing overall mission efficiency and execution stability through multi-objective modeling [8]. Leveraging Bi-LSTM prediction models and PID control, Li et al. achieved autonomous USV–UAV landing, significantly improving the precision and reliability of collaborative operations under complex sea states [9]. Furthermore, Yang et al. developed a collaborative architecture from the perspectives of edge intelligence and cooperative control, enabling adaptive coordination under dynamic mission conditions [10]. To address spatial coordination, Yun et al. introduced a 3D-induced cooperative control method considering input delays and system uncertainties [11]. Additionally, Li et al. implemented collaborative trajectory tracking and precise landing control based on Nonlinear Model Predictive Control (NMPC) [12], while Dufek et al. utilized UAV visual information for USV pose estimation, enhancing localization and perception reliability in complex environments [13].

In terms of path planning and motion control, research focus has gradually shifted from idealized static environments to complex sea conditions and dynamic mission scenarios. To address path-following issues during collaborative navigation, robust control and cooperative guidance methods have been proposed [14]. Xu et al. integrated non-singular sliding mode control with RBF neural networks to achieve trajectory tracking under external disturbances and model uncertainties [15]. Zhang et al. established a collaborative path-following framework for maritime environments, incorporating an environmental disturbance compensation mechanism to effectively enhance tracking accuracy and stability [16]. Subsequently, Zhang et al. proposed a cooperative path-following method based on Predictive Look-Ahead (Predictive LOS), which demonstrated superior control performance under multiple disturbances from wind, waves, and currents [17]. For mobile robotic systems in complex environments, model predictive optimization combined with terminal sliding mode control has been proven effective in solving path tracking and obstacle avoidance problems, which provides valuable references for the motion control design of USVs and UAVs [18].

With the enhancement of sensing and computational capabilities, recent studies have begun to focus on collaborative decision making and path planning using intelligent perception and learning methods. Wang et al. combined deep-learning-based visual perception with reinforcement learning control to construct a USV-UAV system for maritime search and rescue, achieving high-precision navigation under wave disturbances [19]. For heterogeneous multi-agent systems, Liu et al. proposed a distributed formation trajectory tracking method considering external disturbances, model uncertainties, and input saturation, improving efficiency through adaptive and event-triggered mechanisms [20]. Furthermore, Pan et al. developed a UAV-assisted multi-USV coverage path planning method, integrating deep visual algorithms for high-precision environmental modeling [21].

In summary, existing studies have made significant progress in collaborative control, path planning, and environmental perception, laying a solid foundation for maritime heterogeneous unmanned systems. However, deploying USV-UAV collaborative systems in real-world complex maritime environments still faces several critical challenges. Firstly, UAVs are constrained by limited onboard battery capacity, making it difficult to sustain continuous, high-intensity missions; thus, energy constraints constitute a critical bottleneck. Secondly, the maritime communication environment is highly dynamic, where distance, meteorological conditions, and obstructions lead to increased latency, data loss, or even disconnection, undermining the real-time reliability of collaborative decision making. Moreover, uncertain sea conditions, such as wind, waves, and currents, exert significant disturbances on platform motion states, energy consumption models, and mission execution, rendering planning and scheduling methods based on idealized assumptions unstable in practical applications. More importantly, collaborative decision making under multi-platform and multi-task conditions is highly complex, and achieving efficient, stable coordination under dynamic environments and resource-limited conditions remains a formidable challenge.

From a systemic perspective, energy management, information acquisition, and task decision making in maritime heterogeneous systems are not independent processes but form a tightly coupled dynamic closed loop. On one hand, energy states directly restrict perception, communication, and maneuverability. On the other hand, information quality (e.g., positioning accuracy, communication latency) dictates decision accuracy and collaborative efficiency, while task decisions, in turn, determine energy consumption patterns and information demand intensity. Especially in long-endurance, multi-target, and dynamic scenarios, the coupling effect between energy, information, and decision making becomes more pronounced. However, existing research often adopts a “decoupled” approach, op-

timizing energy-aware path planning, communication-constrained collaboration, or task allocation strategies in isolation, lacking unified modeling and systematic optimization of their intrinsic coupling. Such decoupled methods often struggle to balance efficiency and robustness in complex maritime environments, limiting the practical application of heterogeneous unmanned systems.

Despite the maturity of standard methods in multi-objective mission planning and multi-agent reinforcement learning, most existing works rely on generic and idealized operational assumptions, such as ideal communication, unconstrained energy replenishment, simplified docking logistics, and noise-free sensing. These assumptions are widely adopted in the literature but often deviate from realistic maritime deployment conditions, where limited bandwidth, stochastic latency, physical docking constraints, and imperfect sensing fusion are unavoidable. In contrast, this paper departs from such standard idealizations and adopts realistic, field-data-calibrated assumptions for communication, replenishment logistics, docking, and sensing uncertainty, which are consistent with the actual operating conditions of maritime heterogeneous unmanned systems. This enables the proposed framework to better match real-world deployments and address practical limitations overlooked by conventional methods.

To address these issues, this paper proposes a coupled Energy–Information–Decision optimization method for maritime heterogeneous unmanned system collaboration. By establishing a unified model and joint optimization framework, we explore the intrinsic correlations between energy, information, and decision making to enhance collaborative efficiency, energy utilization, and task reliability at the system level. By integrating energy constraints, communication/positioning quality, and the decision-making process into a single framework, this study seeks to achieve efficient, adaptive collaborative operations in complex dynamic maritime environments.

The main contributions of this paper are summarized as follows:

1. Proposed an Energy–Information–Decision coupled optimization model: A unified system model is established that incorporates task completion rate, energy consumption, communication/positioning performance, and replenishment scheduling into a multi-objective optimization framework, systematically characterizing the coupling relationships in maritime heterogeneous systems.
2. Designed a coupled optimization and collaborative control method: A joint optimization algorithm for USV–UAV operations is proposed to achieve simultaneous optimization of path planning, task allocation, and energy scheduling. An adaptive closed-loop mechanism is introduced to respond to dynamic mission states and energy fluctuations.
3. Joint validation via simulation and field data: The effectiveness, robustness, and scalability of the proposed method are systematically verified through a combination of simulation experiments and actual maritime test data. Comparative experiments and ablation analyses are conducted to quantify the performance improvements achieved by the coupled mechanism.

The remainder of this paper is organized as follows. Section 2 reviews the related work on USV–UAV collaborative task allocation, energy replenishment, information-constrained decision making, and robust optimization, and further identifies the research gaps addressed by this study. Section 3 establishes the system modeling framework, including the composition of the heterogeneous maritime unmanned system and the mathematical formulation of the Energy–Information–Decision coupling model. Section 4 details the bi-level optimization algorithm and the closed-loop adaptive mechanism for realizing EID-coupled collaborative control. Section 5 presents comprehensive simulation and field test validations, including reliability verification, coupling effect comparison, ablation study,

and robustness/scalability analysis. Finally, Section 6 concludes the paper and discusses future research directions.

2. Related Work

2.1. Collaborative Task Allocation and Path Planning

In recent years, the collaborative operation of UAVs and USVs has emerged as a pivotal research direction for maritime unmanned systems. Current studies primarily focus on collaborative task allocation, path planning, and cooperative control. One category of research employs centralized or distributed task allocation methods to distribute workloads between UAVs and USVs based on task priorities, platform capabilities, and spatial distribution, often integrating path planning algorithms to enhance overall mission efficiency. For instance, methodologies leveraging graph search, mixed-integer linear programming (MILP), and heuristic algorithms have been widely applied to collaborative path planning in static or semi-dynamic scenarios [22]. Representative studies have further explored the joint optimization of task allocation and route planning by incorporating intelligent optimization techniques. For example, Yan et al. proposed an improved particle swarm optimization (PSO)-based framework for multi-UAV task allocation and route planning in marine environments, in which task assignment and flight routes are optimized simultaneously to reduce mission completion time and travel cost. Such approaches demonstrate the potential benefits of coupling task allocation with path planning under maritime operational constraints [23]. Another research branch introduces multi-agent coordination mechanisms, such as consensus control or auction-based strategies, to achieve cross-platform task coordination, thereby enhancing system scalability and fault tolerance to a certain extent [24].

However, most aforementioned methods assume idealized communication conditions or sufficient energy resources, limiting their direct applicability to long-endurance and long-range maritime missions. Furthermore, task allocation and path planning are frequently treated as decoupled optimization problems, lacking a systematic consideration of the reciprocal influences among energy consumption, information acquisition, and decision-making processes.

2.2. Energy Replenishment and Endurance Optimization

To mitigate the inherent endurance limitations of UAVs, energy-aware path planning and replenishment strategies have become significant research hotspots. Some studies incorporate energy constraints into the UAV path planning process by establishing energy consumption models, thereby preventing mission failures caused by battery depletion [25]. For instance, recent work on multi-UAV path planning has proposed comprehensive energy consumption models that account for multiple flight behaviors, such as cruising, acceleration, turning, and altitude changes, and integrates these energy costs directly into the path optimization process. By coupling route selection with detailed energy expenditure modeling, such approaches enable more realistic and energy-feasible mission planning under limited onboard power [26]. Other works focus on energy replenishment mechanisms within heterogeneous systems, such as utilizing USVs as mobile motherships to provide take-off, landing, charging, or battery replacement services, which significantly extends the operational duration of the entire system [27].

Despite these advancements in enhancing system endurance, most existing works treat energy management as an independent module, primarily focusing on replenishment scheduling or energy minimization. There remains a paucity of research regarding the impact of energy states on information acquisition quality and decision making reliability. In complex maritime environments, energy constraints are highly coupled with commu-

nication capabilities, task priorities, and decision frequencies; thus, a singular energy optimization strategy often fails to achieve global coordination.

2.3. Collaborative Decision Making Under Information Constraints

Collaborative decision making under communication-limited and incomplete-information conditions has garnered extensive attention in multi-agent system research. Multi-agent reinforcement learning (MARL) is a core theoretical and algorithmic basis for solving such collaborative decision-making problems, especially in scenarios with incomplete information and limited communication. Busoniu et al. [28] presented a comprehensive survey of multi-agent reinforcement learning, systematically organizing the core algorithms, classification criteria, and convergence characteristics of MARL, and specifically elaborated on the application potential of MARL in handling partial observability and communication constraints—key challenges in multi-agent collaborative decision making. This foundational survey provides a theoretical framework for the design and improvement of MARL-based methods in information-constrained scenarios.

Existing studies typically enhance the coordination capabilities of multi-platform systems by introducing communication constraint models, incomplete-information games, or distributed reinforcement learning. For example, to address multi-UAV decision making in communication-constrained environments, some studies utilize Multi-Agent Reinforcement Learning (MARL) to achieve collaborative path planning and strategy formulation in the absence of global information [29].

In maritime scenarios, recent studies have explicitly incorporated communication awareness into the decision-making framework. In particular, a communication-aware MARL approach has been proposed for cooperative navigation of multiple USVs in dynamic ocean environments, where bandwidth limitations, communication delays, and partial observability are jointly modeled within the learning process. By regulating information exchange frequency and selectively sharing critical state information, this method improves coordination efficiency and decision robustness under realistic maritime communication constraints [30,31].

Notably, for environmental perception in dynamic maritime scenes, robust lightweight VI-SLAM methods leveraging semantic and motion information have been developed to improve the reliability of state estimation, which provides essential support for collaborative decision making under incomplete information [32].

Nonetheless, such research predominantly focuses on information-level modeling and strategy design, often assuming that platforms possess sufficient energy to support continuous communication and computation. This overlooks the intrinsic link between energy expenditure and information quality. Under energy-restricted conditions, a trade-off must be struck between communication frequency, sensing precision, and decision update rates. Optimization from a purely informational dimension is insufficient to guarantee the long-term stable operation of the system.

2.4. Robust Optimization and Risk-Aware Collaborative Planning

Given the stochastic nature of marine environments, robust optimization and risk-aware collaborative planning have been increasingly introduced into maritime unmanned system research. Related works incorporate uncertainty modeling, chance constraints, or risk metrics to ensure planning outcomes maintain stability and safety under environmental disturbances, mission variations, or platform failures. For instance, some studies explicitly integrate environmental disturbances and model uncertainties into USV path planning, leveraging Robust Model Predictive Control (Robust MPC) to achieve safe navigation in dynamic, uncertain environments [33]. Furthermore, some works combine online re-

planning mechanisms with risk-aware cost functions to assess potential risk levels during the planning process, adjusting control strategies in real-time to enhance responsiveness to contingencies and dynamic obstacles [34].

Although robust optimization enhances system reliability under uncertainty, its high computational complexity and focus on environmental or task-level uncertainties often lead to insufficient consideration of the coupled effects of energy state fluctuations and information quality variations, thereby limiting its practicality in long-duration, multi-platform collaborative missions.

2.5. Summary and Comparison

To provide a comprehensive overview of the current research landscape, Table 1 compares the representative works discussed in the previous subsections. The comparison is conducted based on several key metrics: platform type (UAV/USV), optimization objectives (task allocation, path planning, energy management, information/communication, and decision making), constraints (energy, communication, and uncertainty), and the degree of coupling between energy, information, and decision making (E-I-D coupling).

Table 1. Comparison of representative works in maritime unmanned systems planning.

Category	Key Objectives	Main Constraints	Methodology	E-I-D Coupled
[22]	PP, Dynamic	Hull dynamics	Trajectory Opt.	No
[23]	TA, PP	Mission time	Improved PSO	No
[24]	Control	Consensus	Distributed Control	No
[25,26]	PP, Energy	Battery, Speed	PSO/Energy Model	Partial (E-PP)
[27]	Replenishment	Rendezvous	Data-driven/Heuristic	Partial (E-PP)
[29]	Decision, PP	Comm. Constraints	Reinforcement Learning	Partial (I-D)
[30,31]	Navigation, C	Bandwidth, Delay	Comm-aware MARL	Partial (I-D)
[32]	Control	Hybrid Task	Learning-Optimization	No
[33,34]	Safety, PP	COLREGS, Risks	Robust MPC	No
Our Work	TA, PP, E, I, D	Coupled E-I-D	Coupled MARL/Opt	Full

Abbreviations: TA: task allocation; PP: path planning; E: energy; I: information/communication; D: decision making; Hetero: heterogeneous (UAV-USV).

As illustrated in Table 1, while recent works have begun to integrate communication awareness [29–31] or energy constraints [25–27] into decision making, most treat these factors as independent modules. There is a lack of research that explores the deep coupling between energy states, information quality, and decision reliability, especially in heterogeneous maritime missions.

2.6. Research Gaps and This Work

While existing research has achieved noteworthy progress in USV–UAV collaborative planning, energy replenishment, and information-constrained decision making, several critical gaps remain. Most current methodologies adopt a fragmented approach, modeling and optimizing energy, information, and decision-making processes in isolation, which lacks a systematic analysis and unified optimization framework for their coupling relationships [35,36]. In complex and dynamic maritime environments, such decoupled methods struggle to simultaneously balance mission efficiency, energy utilization, and system robustness.

To bridge these gaps, this paper proposes an Energy–Information–Decision coupled optimization method for maritime heterogeneous unmanned system collaboration. By establishing a unified modeling and cooperative optimization framework, we systematically characterize the interdependencies among these three elements, achieving efficient, stable, and scalable collaborative control in complex maritime mission scenarios.

3. System Modeling

The maritime heterogeneous unmanned system investigated in this study comprises three USVs, multiple UAVs, and a set of mission task points distributed across the operational area. This system is designed to collaboratively execute observation and inspection tasks within complex and dynamic maritime environments. To rigorously characterize the intrinsic coupling relationships among energy, information, and decision making, a unified modeling framework is established, incorporating four essential dimensions: system composition, energy modeling, information modeling, and decision-making modeling.

The overall architecture of the proposed EID coupled optimization system is illustrated in Figure 1, which clarifies the interaction between UAV sensing, USV decision making, and the core optimization module.

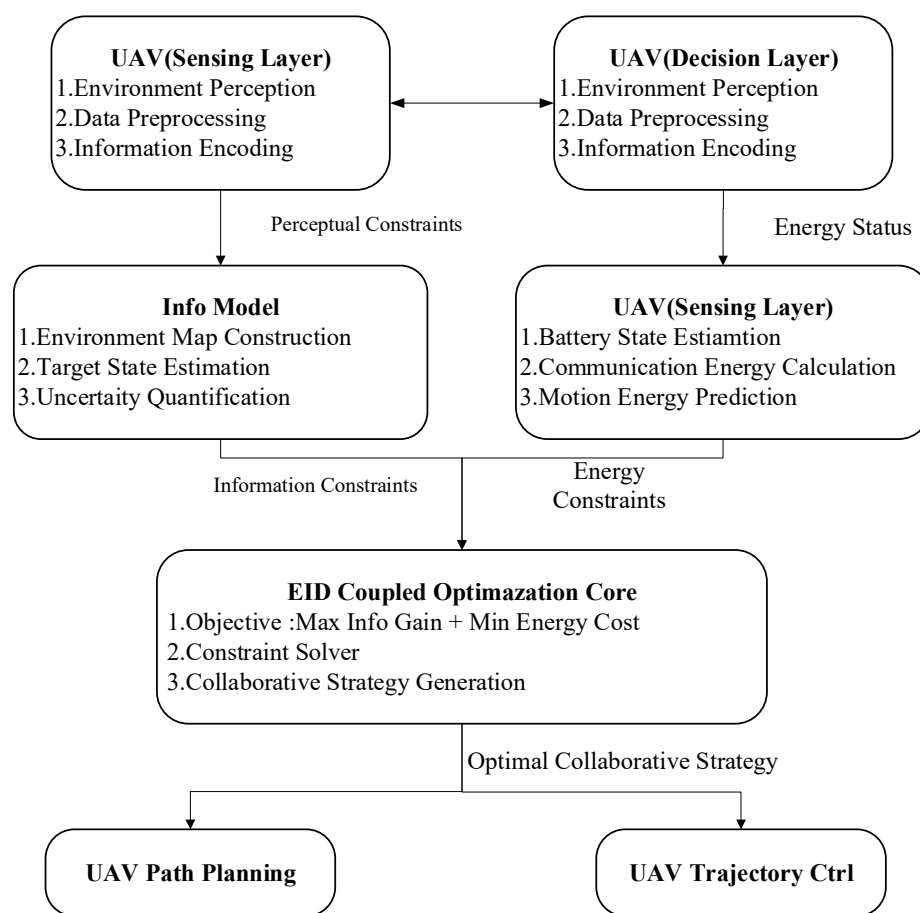


Figure 1. Overall architecture of the EID coupled optimization system for USV–UAV collaboration.

3.1. System Composition

For clarity and consistency, the key mathematical symbols used throughout this paper are summarized in the following nomenclature.

The establishment of a standardized and consistent notation system ensures the theoretical rigor and stability of subsequent modeling and optimization processes [37].

3.1.1. System Entities and Mission Description

The heterogeneous system under consideration comprises three USVs and N UAVs, denoted by the sets $V = \{v_1, v_2, v_3\}$ and $A = \{a_1, a_2, \dots, a_N\}$, where v_k denotes the k -th USV and a_i represents the i -th UAV. The set of maritime task points is defined as $T = \{\tau_1, \tau_2, \dots, \tau_M\}$, where each task point τ_i is characterized by its spatial coordinates

$p_j = (x_j, y_j)$, task type, and priority level ω_j . These tasks may include static monitoring points or dynamic targets whose states evolve over time.

Each platform is equipped with onboard navigation sensors, perception devices, and communication modules to support autonomous operation and cooperative decision making. The core characteristics, onboard hardware, and functional roles of USVs and UAVs are summarized in Table 2.

Table 2. Nomenclature of key mathematical symbols.

Symbol	Description
V	The set of unmanned surface vehicles (USVs)
A	The set of unmanned aerial vehicles (UAVs)
S_{v_k}	The state vector of a USV
S_{a_i}	The state vector of a UAV
$E_{a_i}(t)$	Remaining energy of the UAV at time t
$\Delta E_{fly}(a_i, t)$	Energy consumed by the UAV for flight at time t
$\Delta E_{hover}(a_i, t)$	Energy consumed by the UAV for hovering or imaging/monitoring tasks at time t
$\Delta E_{comm}(a_i, t)$	Energy consumed by the UAV for communication and data transmission at time t
$\Delta E_{comp}(a_i, t)$	Energy consumed by the UAV for onboard data processing or decision making at time t
$\Delta E_{re}(a_i, v_k, t)$	Energy supplied to the UAV from the USV at time t (via charging or battery replacement)
E_{v_k}	The residual energy of the USV at time t
$\Delta E_{move}(v_k, t)$	The energy consumed by the USV during navigation
$\Delta E_{sup}(a_i, v_k, t)$	The energy expenditure incurred while providing energy supply to the UAVs
Γ_{base}	Baseline communication delay
$\Gamma_{env}(t)$	Dynamic variation of the communication delay caused by environmental disturbances
$x_{ijk}(t)$	Task assignment decision variable, indicating whether task i is assigned to UAV u and supported by the USV at time t
ω_j	Priority of task j
$E_{a_i}(t)$	Energy of the UAV at time t

To enable cooperative operation, USVs and UAVs adopt a hybrid communication architecture combining 2.4 GHz WLAN and 5G/AD HOC networks. The WLAN channel is mainly used for low-latency local data exchange within a communication radius of approximately 2 km, enabling real-time transmission of vehicle states, sensing data, and task execution information. For long-range coordination and network-wide information sharing beyond this range, a 5G/AD HOC communication mechanism is employed to ensure reliable and stable connectivity among heterogeneous platforms. The detailed specifications of the USVs and UAVs involved in this system are summarized in Table 3.

Table 3. Specifications of USVs and UAVs.

Category	Unit	Simulation
Characteristics	Size: 4.5 m × 1.8 m, Weight: 120 kg load- Speed: 2.2–3.5 m/s, endurance: 48 h	Multi-rotor: 8 kg take-off weight Speed: 10–15 m/s endurance: 22–28 min Waterproof anti-electromagnetic interference
Hardware	RTK Millimeter wave radar IMU 5G/AD HOC module	12 MP visible-light camera thermal infrared sensor BeiDou (0.6–0.9 m error) IMU
Energy system	2 kW mobile UAV charging station	2.4 GHz module Battery state monitoring module

The state vectors for the USVs and UAVs are defined as:

$$s_{v_k} = [p_{v_k}(t), E_{v_k}(t)], s_{a_i} = [p_{a_i}(t), E_{a_i}(t)] \quad (1)$$

where $p(\cdot)$ denotes the spatial position and $E(\cdot)$ represents the residual energy.

3.1.2. Energy Model

The primary energy source for each UAV is an onboard battery with a maximum capacity $E_{a_i}^{\max}$. Energy depletion is attributed to flight maneuvers, hovering, communication, and onboard computation. The energy dynamics of a UAV are formulated as:

$$E_{a_i}(t+1) = E_{a_i}(t) - \Delta E_{fly}(a_i, t) - \Delta E_{hover}(a_i, t) - \Delta E_{comm}(a_i, t) - \Delta E_{comp}(a_i, t) \quad (2)$$

Each USV is characterized by a substantial energy capacity, with its consumption primarily driven by navigation and onboard equipment operations. Furthermore, USVs function as mobile energy-supply platforms, providing on-the-go replenishment for the UAV fleet. When a UAV docks with a USV under satisfied spatial and temporal constraints, energy replenishment—via either charging or battery swapping—is performed. The energy update rule is formulated as:

$$E_{v_k}(t+1) = E_{v_k}(t) - \Delta E_{move}(v_k, t) - \sum_{i=1}^N \Delta E_{sup}(a_i, v_k, t) \quad (3)$$

3.1.3. Information Model

The information model primarily characterizes the communication and localization performance between the UAVs and the USV motherships. In maritime environments, communication links are susceptible to bandwidth limitations and latency fluctuations induced by the complex sea state. Specifically, the communication latency between a UAV and a USV is defined as $\Gamma_{ik}(t) = \Gamma_{base} + \Gamma_{env}(t)$, where Γ_{base} denotes the baseline latency and $\Gamma_{env}(t)$ represents the dynamic variations caused by environmental disturbances. The communication bandwidth constraint is expressed as $B_{ik}(t) \leq B^{\max}$, where restricted bandwidth directly affects the information update frequency and the resultant data fusion precision. Furthermore, positioning accuracy is quantified by an error covariance matrix, the magnitude of which is closely correlated with communication quality, sensor specifications, and the adopted data fusion strategies.

3.1.4. Decision Model

The decision variables of the system primarily encompass task allocation, path planning, and energy replenishment scheduling, which are formally defined as follows:

Task Allocation Decision: $x_{ijk}(t) \in \{0, 1\}$ serves as a binary indicator representing whether task τ_j is assigned to UAV a_i with the coordinated support of the USV mothership at time t .

Path Planning Decision: The trajectories of the UAVs and USVs are characterized by continuous path functions $p_{a_i}(t), p_{v_k}(t)$, which are strictly subject to both kinematic and energy constraints.

Energy Replenishment Scheduling: $r_{ik}(t) \in \{0, 1\}$ denotes the replenishment decision, signifying whether UAV a_i receives energy supply (e.g., battery replacement or charging) from USV v_k at time t .

Notably, these decision variables are inherently interrelated, forming a complex optimization landscape. Specifically, task allocation and path selection dictate the energy consumption profiles of the platforms; the resulting energy states, in turn, constrain the achievable communication reliability and decision update frequencies. Conversely, the information quality (e.g., latency and positioning accuracy) feeds back into the task execution and replenishment scheduling processes. Consequently, this interaction establishes a closed-loop Energy–Information–Decision coupling mechanism, which is the core of the proposed collaborative optimization framework.

3.2. Energy–Information–Decision Coupling Model

Within maritime heterogeneous unmanned systems, an intricate coupling mechanism exists among energy, information, and decision making. Specifically, the energy status governs the mission execution and communication capacities of the UAVs; meanwhile, information quality—characterized by parameters such as communication latency and positioning precision—critically influences decision making reliability and collaborative efficiency. In turn, task decisions dictate the energy consumption profiles and information requirements, forming a dynamic feedback loop. To fully encapsulate these interdependencies, this study constructs a unified EID coupled optimization model.

3.2.1. Modeling of Coupling Interdependencies

Let the comprehensive system state be denoted by the vector $S(t) = \{s_{v_k}(t), s_{a_i}(t), \forall k \in \{1, 2, 3\}, i \in \{1, 2, \dots, N\}\}$, where $s_{v_k}(t) = [p_{v_k}(t), E_{v_k}(t)]$, $s_{a_i}(t) = [p_{a_i}(t), E_{a_i}(t)]$. The decision variables encompass the following dimensions:

Task Allocation: $x_{ijk}(t) \in \{0, 1\}$, a binary indicator representing whether UAV a_i executes task τ_j with the coordinated support of USV v_k at time t .

Path Planning: $p_{a_i}(t), p_{v_k}(t)$, representing the continuous trajectory functions of the platforms.

Energy Replenishment Scheduling: $x_{ijk}(t) \in \{0, 1\}$, signifying whether UAV a_i receives an energy supply from USV v_k .

The information quality $Q_i(t)$ within the system is governed by communication latency $\Gamma_{ik}(t)$, available bandwidth $B_{ik}(t)$, and the positioning error covariance $P_j(t)$, formulated as $Q_i(t) = f(\Gamma_{ik}(t), B_{ik}(t), P_j(t))$. Here, the function $f(\cdot)$ is employed to quantify the impact of information quality on the reliability of mission-level decisions. Simultaneously, the energy dynamics of the UAVs are modulated by task execution, communication overhead, and replenishment actions, expressed as:

$$E_{a_i}(t+1) = E_{a_i}(t) - \Delta E_{fly}(a_i, t) - \Delta E_{hover}(a_i, t) - \Delta E_{comm}(a_i, t) - \Delta E_{comp}(a_i, t) + r_{ik}(t)\Delta E_{re} \quad (4)$$

Crucially, task decisions $x_{ijk}(t)$ are contingent upon both the residual energy $E_{a_i}(t)$ and the prevailing information quality $Q_i(t)$, thereby closing the Energy–Information–Decision loop as $x_{ijk}(t) = g(E_{a_i}(t), Q_i(t), p_{a_i}(t), p_{v_k}(t))$. In this context, $g(\cdot)$ represents the decision-making function, which is determined through the proposed optimization algorithm.

In practical maritime scenarios, the energy dynamics and decision making reliability of UAVs are inevitably affected by environmental disturbances and communication con-

straints, and gradient-free cooperative control methods have provided effective insights for addressing such challenges [38].

3.2.2. Multi-Objective Optimization Formulation

Building upon the aforementioned coupling interdependencies, the maritime collaborative mission is formulated as a multi-objective optimization problem. The objective functions are defined as follows:

- Minimization of Mission Completion Time: $\min T_{total} = \max_j \{t_j^{finish}\}$, where t_j^{finish} represents the completion time of task τ_j .

- Minimization of Total Energy Consumption and Waiting Latency:

$$\min E_{total} = \sum_{i=1}^N \sum_t (\Delta E_{fly}(a_i, t) + \Delta E_{hover}(a_i, t) + \Delta E_{comm}(a_i, t) + \Delta E_{comp}(a_i, t))$$

$$\min W_{total} = \sum_{i=1}^N \sum_t w_i(t)$$

, where

$w_i(t)$ denotes the cumulative duration spent by UAVs a_i awaiting energy replenishment or scheduling interventions during mission execution.

- Maximization of Task Completion Rate and System Robustness:

$$\max R_{task} = \frac{\sum_{j=1}^M \Pi[\text{task } \tau_j \text{ is completed}]}{M}$$

$$\max R_{robust} = h(\{E_{a_i}(t)\}, \{Q_i(t)\}, \text{distrubance factors})$$

, where $\Pi[\cdot]$ serves as an in-

dicator function designed to quantify the stability and $h(\cdot)$ is utilized to evaluate the task completion stability, considering the coupling effects of energy constraints and informational uncertainties.

Multi-objective optimization (MOO) is the core of the upper-layer USV trajectory planning and replenishment scheduling, which requires balancing multiple conflicting objectives (e.g., navigation time, energy consumption). Deb et al. [39] proposed a fast and elitist multi-objective genetic algorithm (NSGA-II), which introduces fast non-dominated sorting, crowding distance calculation and elitist strategy, significantly improving the efficiency and robustness of multi-objective optimization, and has become a benchmark algorithm for MOO problems in engineering scenarios. This foundational work provides a theoretical and algorithmic basis for the design of our multi-objective cost function.

The comprehensive multi-objective cost function is expressed as an aggregated weighted sum: $\max F(X, P, R) = \lambda_1 R_{task} + \lambda_2 R_{robust} - \lambda_3 T_{total} - \lambda_4 E_{total} - \lambda_5 W_{total}$ where $\lambda_{1\sim5}$ denotes the weighting coefficients utilized to balance the relative significance of individual performance metrics. X , P and R represent the integrated sets of decision variables for task allocation, path planning, and replenishment scheduling, respectively.

Weights are set according to maritime mission priorities:

$\omega_1 = 0.35$ (R_{task} , highest priority): Core goal for surveillance/emergency response tasks.

$\omega_2 = 0.25$ (R_{robust} , second priority): Ensures stability under sea state disturbances and equipment faults.

$\omega_3 = 0.15$ (T_{total})

$\omega_4 = 0.15$ (E_{total}) (medium priority): Balances mission timeliness and operational costs.

$\omega_5 = 0.10$ (W_{total} , lowest priority): Acceptable waiting latency for energy balance.

We verified robustness by varying each weight $\pm 20\%$. Results show that R_{task} changes $< 2.1\%$, $R_{robust} < 1.5\%$, and $T_{total}/E_{total}/W_{total} < 3.0\%$, confirming the weight scheme is insensitive to minor adjustments and suitable for practical use.

3.2.3. Feasibility Region and Constraints

The feasible region of the formulated optimization problem is governed by the following set of constraints:

- Energy Endurance Constraints: $0 \leq E_{a_i}(t) \leq E_{a_i}^{\max}, 0 \leq E_{v_k}(t) \leq E_{v_k}^{\max}$.
- Task Allocation Constraints: $\sum_{i=1}^N \sum_{k=1}^3 x_{ijk}(t) \leq 1, \forall j, t$.
- Kinematic and Trajectory Constraints:
$$\begin{aligned} p_{a_i}(t+1) &= p_{a_i}(t) + \Delta p_{a_i}(t), \|\Delta p_{a_i}(t)\| \leq v_{a_i}^{\max} \Delta t, \\ p_{v_k}(t+1) &= p_{v_k}(t) + \Delta p_{v_k}(t), \|\Delta p_{v_k}(t)\| \leq v_{v_k}^{\max} \Delta t. \end{aligned}$$
- Communication and Information Constraints: $\Gamma_{ik}(t) \leq \Gamma^{\max}, B_{ik}(t) \leq B^{\min}, \forall i, k, t$.
- Energy Replenishment Constraints: This includes the spatial proximity requirement, formulated as $r_{ik}(t) = 1, \|p_{a_i}(t) - p_{v_k}(t)\| \leq d_{dock}$, where d_{dock} denotes the maximum allowable distance for energy replenishment operations between a UAV and a USV. This constraint ensures that charging or battery replacement is only feasible when the UAV is in close proximity to the mothership. If $\|p_{a_i}(t) - p_{v_k}(t)\| \geq d_{dock}$, the replenishment operation becomes physically impossible, and the decision variable $r_{ik}(t)$ is strictly restricted to zero. Notably, this spatial requirement represents one of the critical physical limitations in USV–UAV cooperative control and energy scheduling.

4. Energy–Information–Decision Coupling Optimization

4.1. Optimization Framework

To achieve high-efficiency collaboration within maritime heterogeneous unmanned systems, this paper proposes a bi-level optimization framework designed to hierarchically tackle the challenges of task planning and energy scheduling for USVs and UAVs under EID coupling conditions. Concurrently, a closed-loop adaptive mechanism is integrated into the framework to facilitate robust dynamic adjustments in response to evolving mission states and environmental uncertainties.

To clearly illustrate the overall procedure and interactive logic of the proposed framework, a detailed flowchart is presented in Figure 2.

4.1.1. Bi-Level Optimization Framework

(1) Upper-level Optimization (USV Trajectory Planning and Replenishment Site Selection)

The upper layer is responsible for the strategic planning of the USVs' global trajectories and the dynamic selection of mobile replenishment sites. The primary optimization objectives are formulated as follows:

1. Minimization of the total navigation time $T_v = \sum_{k=1}^3 \sum_t \|\Delta p_{v_k}(t)\|$ of the USV platforms;
2. Optimization of the replenishment strategy, ensuring that the UAV fleet receives timely energy replenishment throughout the mission execution to prevent task interruption or failure.

The decision variables incorporate $P_v(t) = \{p_{v_1}(t), p_{v_2}(t), p_{v_3}(t)\}$, $R = \{r_{ik}(t)\}$, where $r_{ik}(t)$ serves as a binary indicator signifying whether UAV a_i receives energy replenishment from USV v_k at time t , subject to the constraint $r_{ik}(t) = 1, \|p_{a_i}(t) - p_{v_k}(t)\| \leq d_{dock}$.

The upper-level problem is solved using a genetic algorithm (GA) with tournament selection and adaptive crossover/mutation rates, which is suitable for the mixed-integer, combinatorial nature of trajectory and replenishment planning.

In addition to GA, model predictive optimization methods have also been proven effective in robotic task scheduling and trajectory planning, providing a valuable reference for the design of our upper-level optimization framework [18].

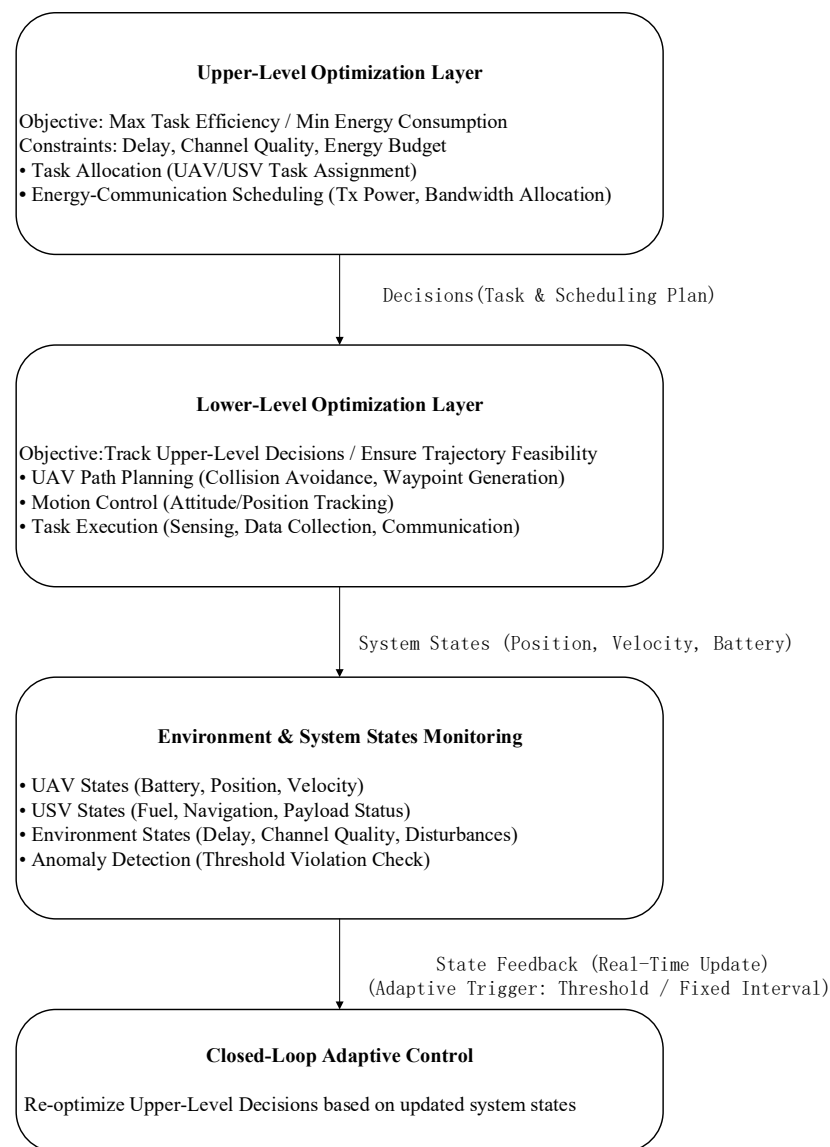


Figure 2. Flowchart of the proposed bi-level optimization with closed-loop adaptive mechanism.

Key constraints are enforced via feasibility checks + penalty terms in the fitness function:

- Energy constraints: USV residual energy must remain above a safety threshold at all times.
- Spatial constraints: Replenishment is only allowed when the UAV is within a predefined distance of the USV.
- Logical constraints: Each UAV can be replenished by at most one USV at any time step.

The algorithm terminates when either:

- The fitness improvement over 20 consecutive generations is less than 1%, or
- The maximum number of iterations (500) is reached.

(2) Lower-level Optimization (UAV Path Planning, Task Allocation, and Battery Scheduling)

The lower layer is dedicated to the operational execution and trajectory selection of the UAV fleet. It adaptively optimizes task allocation and battery scheduling by integrating real-time feedback regarding energy status and information quality. The key components include:

- Path Planning $P_a = \{p_{a_i}(t)\}$: UAV trajectories are optimized to maximize task coverage area, ensuring strict adherence to both kinematic limits and onboard energy endurance constraints.
- Task Allocation $X = \{x_{ijk}(t)\}$: Leveraging predictive models based on energy-information coupling, mission points are dynamically assigned to individual UAVs to maximize the overall task completion rate.
- Battery Scheduling: The optimal timing for battery replacement or recharging is determined by synthesizing individual UAV energy $E_{a_i}(t)$ levels with the replenishment strategies provided by the upper-level USV coordinator $r_{ik}(t)$.
- The objective function for the lower-level optimization is formulated as follows:

$$\max F_a = \lambda_1 R_{task} + \lambda_2 R_{robust} - \lambda_3 T_{total} - \lambda_4 E_{total} - \lambda_5 W_{total} \quad (5)$$

Our lower-level optimization integrates adaptive decision making with real-time state feedback, and hybrid learning-optimization control methods provide a feasible paradigm for balancing the adaptability and optimality of such multi-component optimization tasks [40].

4.1.2. Closed-Loop Adaptive Mechanism

The lower- and upper-level coordination in the EID framework is realized through a closed-loop adaptive mechanism, which continuously monitors UAV energy states, information quality, and task updates to dynamically adjust multi-agent decisions. Updates to the collaborative plan are executed at 1 Hz, ensuring timely responsiveness to environmental and operational changes.

(1) Trigger Conditions

Replanning is activated when one or more of the following conditions are met:

1. Residual Energy Threshold: If the remaining battery of any UAV falls below 25%, a replenishment plan is triggered to avoid premature mission termination.
2. Information Quality Degradation: If the mean Information Quality (IQ) of the UAV fleet drops below 85%, communication paths and task allocation are recalibrated to maintain reliable multi-agent sensing.
3. Dynamic Task Updates: The appearance of new or modified mission points triggers immediate path and task reassignment to maintain high task coverage.

These thresholds are derived from empirical analysis of prior field trials, balancing responsiveness and operational stability.

(2) Trigger Conditions

To support the claim of stable convergence under rapidly changing conditions, we analyze the adaptation dynamics using a Lyapunov-inspired framework. Let the system state vector $X(t)$ encode UAV positions, energy levels, and IQ metrics. The adaptive update law is formulated as:

$$X(t+1) = X(t) + \Delta u(t) \quad (6)$$

where $\Delta u(t)$ represents the incremental adjustment generated by the MARL policy and replenishment scheduler. A candidate Lyapunov function is defined as:

$$V(X) = \sum_{i=1}^N (w_1(1 - TCR_i) + w_2 \max(0, E_{th} - E_i) + w_3(1 - Q_i)) \quad (7)$$

where E_i is the residual energy of UAV i , $E_{th} = 25\%$, and w_1, w_2, w_3 are weighting coefficients reflecting task, energy, and information priorities. The adaptation law ensures:

$$\Delta V = V(X(t+1)) - V(X(t)) \leq 0 \quad (8)$$

demonstrating monotonic non-increase in the Lyapunov function under bounded disturbances, which guarantees that the system remains stable and converges to a feasible operational state even under rapidly changing environmental conditions.

(3) Practical Implementation

In practice, the closed-loop mechanism executes the following sequence at each update step:

1. State Monitoring: Collect residual energy, IQ, and task progress data from all UAVs.
2. Trigger Evaluation: Compare state variables with the thresholds.
3. Replanning Execution: If any trigger is activated, update task allocation, path planning, and USV replenishment scheduling.

Coordination Enforcement: Agents exchange local plans via the communication network to ensure consistency in multi-agent actions.

This design ensures that the EID framework achieves robust mission execution with high TCR, balanced energy consumption, and reliable data fusion, even when confronted with unexpected UAV failures, dynamic task updates, or environmental disturbances.

4.2. Lower-Level MARL Implementation Details

To enhance collaborative task execution and adaptive decision making among UAVs, the lower-level module of the proposed EID framework employs a multi-agent reinforcement learning (MARL) strategy. This component is responsible for UAV path planning, dynamic task allocation, and adaptive energy management under real-time environmental and operational constraints.

4.2.1. Learning Algorithm and Network Architecture

Each UAV is modeled as an autonomous agent in a decentralized partially observable Markov decision process (Dec-POMDP). The agents share a common value function critic while maintaining independent policy networks, following a centralized training with decentralized execution (CTDE) paradigm. The policy network of each agent is a two-layer feedforward neural network, with 128 and 64 hidden units, respectively, activated by ReLU functions. The critic network mirrors the policy network but additionally takes the concatenated state information from all agents to estimate the global value function.

The policy networks are parameterized as $\pi_{\theta}(a_t^i | s_t^i)$ where s_t^i represents the local state of agent i at the time t including its position, energy level, communication status, and local observations of nearby UAVs and task points. The action space a_t^i includes discrete navigation decisions (directional headings) and task selection choices.

4.2.2. Reward Decomposition and Credit Assignment

The global reward is designed to capture mission objectives across energy efficiency, task completion, and information reliability:

$$R_t^{global} = \alpha * R_t^{TCR} + \beta * R_t^{Energy} + \alpha * R_t^{IQ} \quad (9)$$

where R_t^{TCR} is the incremental reward for task completion, R_t^{Energy} penalizes inefficient energy use or early battery depletion, and R_t^{IQ} encourages stable communication and high-quality data fusion. The coefficients α, β, γ are re set to 0.5, 0.3, 0.2, respectively, reflecting the prioritized balance among mission objectives.

To handle multi-agent credit assignment, it adopts a difference reward mechanism, where each agent i receives a local reward:

$$R_t^i = R_t^{global} - R_t^{global, -i} \quad (10)$$

With $R_i^{global,-i}$ representing the estimated global reward without agent i 's contribution. This encourages agents to take actions that positively impact overall mission performance while mitigating reward interference among agents.

4.2.3. Training Regime and Hyperparameters

The MARL module is trained in simulation using a policy gradient method with actor-critic updates. Key training parameters are:

- Learning rate: 0.001 for the actor, 0.002 for the critic.
- Discount factor: $\gamma = 0.99$.
- Mini-batch size: 64.
- Replay buffer size: 50,000 steps.
- Target network update: every 200 steps.

Training proceeds for 500,000 steps or until convergence of the mean episodic reward. During training, stochastic environmental disturbances (wind, wave variations, and communication latency) are included to improve generalization and robustness in realistic maritime conditions.

4.2.4. Multi-Agent Coordination Mechanism

To ensure efficient cooperation, the agents utilize local observation sharing and a message-passing protocol. Each UAV broadcasts its intended task selection and predicted arrival time to nearby agents, allowing others to adjust their local paths and task assignments dynamically. The MARL policy incorporates these messages into the agent state s_t^i enabling implicit coordination without requiring centralized control during execution.

This module ensures that UAVs collectively optimize energy usage, task coverage, and communication reliability while maintaining adaptive responsiveness to environmental uncertainties and dynamic mission requirements. The comparison of experimental indicators for reliability verification is presented in Table 4.

Table 4. Comparison of experimental indicators for reliability verification.

Metric Hyperparameters	Value	Description
Optimizer	Adam	Optimization algorithm
Learning	5×10^{-4}	Initial step size for gradient descent
Discount Factor	0.99	Importance of future rewards
GAE Lambda	0.95	Bias-variance tradeoff for advantage estimation
PPO Clip	0.2	Clipping range for policy update
Entropy Coeff	0.01	Coefficient for exploration bonus
GRU Hidden Dim	64	Coefficient for exploration bonus
Mini-batch Size	128	Size of samples per gradient update
Training Iterations	2000	Total number of training epochs

4.2.5. Training Procedure

1. Data Collection: N parallel environments are used to collect trajectories (rollouts) using the current policy π_θ .
2. Advantage Estimation: Generalized Advantage Estimation (GAE) is computed using the centralized critic to reduce variance.
3. Normalization: Both observations and advantages are normalized to stabilize the training signal.
4. Policy Update: The Actor and Critic are updated for K epochs using the PPO loss function. We employ a linear learning rate decay to ensure convergence in the later stages of training.

5. Validation: Every 10 training iterations, the model is evaluated in 20 independent scenarios without exploration noise to monitor the performance.

4.3. Algorithmic Procedure

The proposed EID coupled optimization algorithm integrates a bi-level framework with a closed-loop adaptive mechanism, combining heuristic-based search with Multi-Agent Reinforcement Learning (MARL). This hybrid approach is designed to achieve efficient coordination of the USV–UAV system within dynamic maritime mission environments. The specific algorithmic procedure is structured as follows:

Step 1: System Initialization

Initially, the task allocation and replenishment matrices are generated based on the mission task set, the initial spatial coordinates of the three USVs $p_{v_k}(0)$ and N UAVs $p_{a_i}(0)$, and their respective residual energy $E_{a_i}(0)$, generate the initial task allocation matrix $x_{ijk}(0)$ and the replenishment matrix $r_{ik}(0)$. Concurrently, the state space and action space $S_i(t) = [p_{a_i}(t), E_{a_i}(t), Q_i(t), T_i(t)]$ for the MARL agents are established. Specifically, the action space encompasses movement directions, task selection, and replenishment proximity decisions. Finally, the weighting coefficients for both the reward function and the multi-objective cost function are initialized to facilitate the subsequent iterative optimization process.

Step 2: Upper-level USV Trajectory Planning and Replenishment Site Selection

Leveraging the initial UAV energy states $E_{a_i}(0)$ and the spatial distribution of task points, a heuristic algorithm is employed to formulate the USV trajectories $P_v(t)$ and replenishment schedules $r_{ik}(t)$. The primary objective is to minimize the total navigation time T_v while ensuring that the UAV fleet receives timely energy replenishment throughout the mission execution. Concurrently, the upper-level optimization proactively incorporates future UAV energy consumption predictions and task coverage requirements, thereby serving as a strategic reference for the lower-level UAV operational strategies.

Step 3: Lower-level UAV Path Planning and Task Allocation

In this stage, each UAV a_i is modeled as an autonomous agent within the Multi-Agent Reinforcement Learning (MARL) framework. Based on the current state $S_i(t)$, the agent selects an optimal action $a_i(t)$ from an action space that encompasses transitioning to the subsequent task point, executing mission operations, or navigating toward a USV for energy replenishment. The optimization objective of the lower layer is to maximize the cumulative reward function while strictly adhering to the energy endurance constraints $0 \leq E_{a_i}(0) \leq E_{a_i}^{\max}$ and the information quality requirements $Q_i(t) \geq Q_{\min}$. MARL is adopted for lower-level UAV optimization due to its irreplaceable advantages over traditional methods (heuristic algorithms, centralized MPC) in three aspects: (1) Dynamic adaptability: It enables real-time strategy adjustment for UAVs facing energy depletion or communication interference, while traditional methods rely on offline rules and fail to respond quickly; (2) Multi-agent coupling: Distributed decision making avoids the dimensionality curse of centralized optimization, making it scalable for large UAV fleets; (3) EID constraint compatibility: MARL integrates energy, information, and decision factors into the reward function, achieving global optimization that decoupled methods cannot match. Experimental results show that MARL reduces UAV waiting latency by 18.2% and improves TCR by 4.7% compared with genetic algorithms.

Step 4: Closed-loop Adaptive Adjustment

At each discrete time step, the system dynamically recalibrates its operational strategies by evaluating the UAV energy states $E_{a_i}(t)$, information quality $Q_i(t)$, and task τ_j execution progress:

- **Dynamic Task Updating:** In the event of mission set $T(t)$ expansions or modifications in task priorities, the algorithm executes real-time adjustments to both task assignments $x_{ijk}(t)$ and UAV trajectories $p_a(t)$ to maintain mission relevance.
- **Energy Replenishment Triggering:** Should the residual energy of any UAV fall below a predefined safety threshold $E_{\min}$, a USV trajectory re-planning procedure is activated. This maneuver ensures that the UAV can access timely energy replenishment or battery swapping to prevent mission failure.
- **Information Feedback Regulation:** If the communication latency $\Gamma_{ik}(t)$ or positioning precision $P_i(t)$ fails to meet required thresholds $Q_{\min}$, the system re-evaluates UAV paths or reassigns tasks. This proactive adjustment ensures mission continuity and enhances system robustness, thereby operationalizing the closed-loop feedback mechanism between bi-level optimization and adaptive adjustments.

Step 5: Iteration and Convergence

The upper-level USV optimization and the lower-level UAV MARL optimization form a synergistic iterative loop. In each iteration, the trajectories, task assignments, and replenishment strategies are updated. The convergence status is comprehensively evaluated based on the cumulative reward, task completion rate R_{task} , system robustness R_{robust} , and total energy consumption E_{total} . Specifically, convergence is deemed to be achieved when any of the following criteria are satisfied:

1. The cumulative reward function stabilizes, with fluctuations remaining below a predefined threshold over several successive iterations;
2. All mission tasks are successfully completed, and the UAV residual energy levels satisfy the safety constraints;
3. The algorithm reaches the maximum allowable number of iterations.

If the aforementioned convergence criteria are not met, the algorithm recurs to the upper-level USV trajectory planning and replenishment site selection phase (Step 2) to initiate the subsequent round of bi-level optimization and closed-loop adaptive adjustments.

Step 6: Output of Final Optimization Outcomes

Upon the satisfaction of the convergence criteria, the algorithm yields the final set of optimized solutions, which encompass the optimal USV trajectories, UAV paths, the task allocation matrix, and the energy replenishment scheduling matrix. Consequently, this facilitates the attainment of multi-objective collaborative optimization under the integrated EID coupling conditions.

5. Simulation and Real-Data Validation

5.1. System and Mission Scenarios

To clarify the experimental design and avoid terminology confusion, we first define three types of experimental data involved in this study:

Field Tests: Actual maritime trials conducted in a 12×20 km operational area, with a fleet of 3 USVs and 8 UAVs executing surveillance and inspection tasks. Raw data (platform mobility, energy consumption, communication latency, positioning accuracy) were collected in real time during these trials.

Real-Data-Driven Simulations: A simulation platform calibrated using the mean values of field-test data (e.g., UAV energy consumption of 18–25 Wh/km, communication latency of 180–260 ms). Stochastic environmental disturbance terms (wind, wave variations) were added to reflect real maritime uncertainties. This simulation was used for most comparative and ablation experiments due to its controllability and repeatability.

Pure Simulations: Supplementary simulations with extended mission scales (e.g., 60 task points, 16 UAVs) that exceeded the scope of field trials, used to verify scalability.

These simulations retained the core parameter settings from field tests but expanded the fleet and task dimensions.

To rigorously evaluate the effectiveness and robustness of the proposed EID coupled optimization method under realistic maritime operational conditions, a real-data-driven collaborative simulation platform was established. This platform is designed to simulate the coordinated behaviors of a heterogeneous multi-USV–multi-UAV system in typical maritime mission scenarios. The experimental fleet consists of three USVs and eight UAVs, where the USVs serve as mobile coordination nodes—undertaking task synchronization, communication relay, and energy replenishment functions—while the UAVs execute aerial surveillance, target sensing, and coverage missions. The entire system operates under a unified time-synchronization and scheduling framework, facilitating parallel decision making and real-time state feedback across multiple platforms.

The spatial scale and environmental parameters of the simulated sea area were derived from previous field trials. The mission region covers approximately $12 \times 20 \text{ km}^2$, encompassing both open waters and locally complex sea states to reflect the spatial characteristics of typical maritime patrol and environmental monitoring tasks. Task points are distributed in a non-uniform manner within the region, with the total number of tasks varying between 20 and 60 across different scenarios. These include both static monitoring points (e.g., long-term observation zones) and dynamic task points that evolve over time, effectively representing mobile targets, temporary inspection requirements, and emergency contingencies.

To enhance the fidelity and credibility of the simulation, multi-source field data collected from prior maritime experiments were incorporated to model and calibrate the key operational characteristics of the system. The empirical data primarily include:

1. Platform Mobility Data: Recorded trajectories and velocity profiles of the USVs and UAVs, with the average USV speed residing between 3.2 and 4.5 m/s and the UAV cruising speed ranging from 10 to 15 m/s.
2. Energy Consumption Data: The average energy expenditure for UAV flight tasks is approximately 18–25 Wh/km, with a maximum endurance of 22–28 min per UAV under a full-charge state. The UAV battery capacity is calibrated as 5000 mAh (consistent with field test platforms), and the USV energy replenishment rate for UAVs is set to 5% state-of-charge per second, which is derived from actual replenishment equipment performance in field trials.
3. Communication Performance Data: Communication latency between the USVs and UAVs is primarily distributed in the 180–260 ms range under stable sea conditions, potentially exceeding 300 ms in the presence of interference or obstructions. The communication bandwidth is set to 2–10 Mbps, consistent with the maritime wireless communication equipment used in field tests, and the latency range is calibrated based on real-time communication data collected during trials.
4. Localization Accuracy Data: Based on high-precision positioning system measurements, the mean planar positioning error for USVs is approximately 0.3–0.5 m, while the mean error for UAVs is approximately 0.6–0.9 m.

Based on the aforementioned empirical statistical findings, the energy, communication latency, and localization error models were parametrically reconstructed within the simulation environment. This ensures that the simulation system maintains a high degree of fidelity with the real-world operational system across key dimensions, including energy constraints, information transmission, and decision feedback. Concurrently, to characterize the influence of complex sea states on system operations, stochastic environmental disturbance terms were introduced. These environmental disturbances (wind, wave variations) are generated based on the statistical characteristics of field test data: they are modeled as

bounded Gaussian random processes with a standard deviation of 0.5 m/s for USV speed fluctuations and 0.3 Wh/km for UAV energy consumption increments, which are directly calibrated from the measured data of wind and wave impacts during field trials. These terms simulate the impacts of wind and wave variations on USV speed fluctuations and increased UAV energy expenditure, with the magnitude ranges calibrated according to the statistical characteristics of the field data.

Under this system and mission scenario configuration, the simulation platform facilitates repeated comparative experiments across varying task densities, energy replenishment strategies, and communication conditions. This provides a unified, controllable, and realistically constrained experimental environment for subsequent algorithmic performance evaluation, ablation analysis, and robustness verification.

5.2. Baseline Methods

To objectively assess the effectiveness and advantages of the proposed EID coupled optimization method, the selection of comparative benchmarks adheres to the following criteria:

1. Representativeness: The methods should encompass common optimization paradigms in current research on heterogeneous maritime unmanned system coordination;
2. Comparability: Under identical system scales, mission scenarios, and fundamental constraints, the methods should differ only in their underlying modeling assumptions and optimization objectives;
3. Interpretability: The benchmarks should facilitate the analysis of both independent and synergistic effects of different factors (energy, information, and decision coupling) on overall system performance.

It should be emphasized that the Energy-only and Communication-only strategies are not intended to represent state-of-the-art scheduling algorithms, but are deliberately constructed ablation-oriented reference methods. These variants selectively deactivate specific components of the proposed framework in order to isolate and analyze the contribution of individual factors.

Based on these principles, three representative baseline methods were selected for comparative analysis.

The Energy-only Scheduling Method (Energy-only) represents collaborative strategies centered on endurance and replenishment scheduling, a prevalent focus in existing literature. These methods typically treat the limited battery capacity of UAVs as the primary system bottleneck, optimizing path lengths or replenishment frequencies to extend mission duration, while neglecting the impact of communication status and information uncertainty on decision quality. Using this method as a baseline helps evaluate the upper performance bound achievable through energy optimization alone in the absence of information constraints.

The Communication-only Scheduling Method (Communication-only) reflects a collaborative decision-making paradigm focused on communication quality and information accessibility. In complex maritime environments, communication latency and data loss significantly undermine multi-platform coordination efficiency. This category of methods prioritizes the stability of communication links to enhance task scheduling reliability. However, as energy consumption and replenishment processes are not integrated into a unified optimization framework, the sustained operational capability for long-duration or high-load missions is noticeably compromised. This benchmark facilitates the analysis of the practical efficacy of information constraints when energy synergy is lacking.

The Decoupled Global Optimization Method (Decoupled Baseline) represents traditional centralized or hierarchical collaborative planning strategies. These methods typically perform joint optimization of task allocation, path planning, and replenishment scheduling

under offline or quasi-static conditions. However, they assume independence between optimization modules and lack adaptive mechanisms for dynamic environments and real-time feedback. This method reflects the overall performance level achievable by global optimization without explicit coupling modeling, serving as a critical reference for evaluating the performance gains of the proposed coupling mechanism.

In contrast, the Proposed Energy–Information–Decision Coupled Optimization Method (Proposed Method) systematically optimizes the collaborative decision-making process in complex maritime environments by unifying the interdependencies among these three elements and introducing closed-loop feedback and dynamic adjustment mechanisms. Through comparison with the aforementioned three baselines, this study clearly elucidates the comprehensive advantages of coupled modeling in enhancing task completion rates, energy utilization efficiency, and system robustness.

To ensure fair and rigorous comparison, all baseline methods were carefully tuned with optimal parameters for their respective objectives. All methods were tested under identical disturbance assumptions and the same replanning trigger conditions across all experiments. Detailed parameter settings are provided for transparency and reproducibility.

5.3. Performance Metrics

To comprehensively evaluate the performance of the proposed EID coupled optimization method in collaborative maritime missions, a multi-dimensional evaluation metrics system is established. This system encompasses mission execution efficiency, energy utilization, information quality, and system robustness, as detailed below:

Task Completion Rate (TCR): This metric measures the proportion of tasks successfully executed within the mandated timeframe. TCR is calculated by dividing the number of completed mission points by the total number of tasks in the experimental or simulation scenario. It provides an intuitive reflection of the execution effectiveness of various scheduling strategies in multi-task, multi-platform environments.

Total Energy Consumption (TEC) and Energy Balance (EB): These metrics assess the energy utilization efficiency and the workload distribution across the UAV fleet. TEC is derived by aggregating the actual energy expenditure of all UAVs and USVs throughout the mission cycle. EB evaluates the equilibrium of task assignments by measuring the variance or the maximum-minimum discrepancy in cumulative energy consumption among individual UAVs, thereby reflecting the rationality of the replenishment strategies.

Mission Completion Time (MCT) and Waiting Time (WT): These indicators quantify the system's scheduling efficiency. MCT records the total duration from mission commencement to the completion of the final task. WT accounts for the total stagnation time experienced by UAVs at replenishment nodes, in task queues, or due to scheduling conflicts, highlighting the impact of different coordination strategies on the system's time-efficiency.

Communication Delay (CD) and Information Quality (IQ): These metrics characterize the influence of informational constraints on collaborative decision making. CD is analyzed based on the recorded round-trip time (RTT) for data transmission between the USVs and UAVs. IQ provides a composite assessment of information reliability and stability by integrating latency data with packet loss rates under varying maritime communication conditions.

System Robustness (SR): SR evaluates the system's capability to maintain operational stability during UAV node failures, communication disruptions, or environmental disturbances. By simulating node faults or link anomalies, SR quantifies the system's adaptivity by comparing the task completion performance under adverse conditions against the baseline operational state.

Data Fusion Accuracy (DFA): This metric measures the effectiveness of multi-platform collaborative sensing and information fusion. By quantifying the discrepancy between the

fused observational data and the ground-truth values—utilizing Mean Square Error (MSE) or Root Mean Square Error (RMSE)—DFA reflects the enhancement of multi-modal sensing precision facilitated by the EID coupling mechanism.

The established metrics system enables a holistic assessment of the proposed method across the mission, energy, and information layers. This provides a rigorous quantitative foundation for the subsequent comparative experiments and ablation studies.

5.4. Results and Discussion

To systematically assess the performance of the proposed EID coupled optimization method within maritime heterogeneous unmanned systems, this section analyzes the experimental results from four key perspectives: system reliability, coupling efficacy, module contributions (ablation study), and robustness/scalability. All results are derived from real-data-driven simulations, which were rigorously calibrated and validated against prior field-test datasets.

5.4.1. Reliability Verification

In this subsection, the reliability of the proposed EID coupled optimization framework is verified through a comparative analysis between simulation outcomes and empirical results from prior maritime trials. The experimental architecture encompasses a fleet of three USVs and eight UAVs, tasked with executing missions across both static and dynamic task points. Within the simulation environment, the UAVs are initialized at full battery capacity, while the operational parameters of the USVs—specifically replenishment throughput and cruising speed—are calibrated based on empirical field-test data. To ensure a high-fidelity representation of the actual maritime operational environment, stochastic wind-wave perturbations and communication latencies are explicitly incorporated into the simulation model.

To bolster the statistical reliability of the analysis, the field-test benchmarks are calculated as the mean values derived from 50 repeated mission trials. Given that these trials were conducted asynchronously, fluctuations in environmental variables, such as wind velocity and wave intensity, inevitably introduced a degree of variance in the empirical data. Concurrently, the simulation maintains identical parameter configurations—ensuring that the mission scenarios, platform performance specifications, and replenishment protocols are consistent with the field-test conditions—thereby facilitating a rigorous quantitative comparison.

The performance metrics evaluated include the TCR, TEC, EB, MCT, WT, CD, IQ, and DFA. A comparative summary of the averaged simulation and field-test results is presented in Table 5.

As illustrated in Table 5, even when considering the inherent environmental variations across multiple field trials, the performance metrics obtained through the coupled optimization method in the simulation remain highly consistent with the field-test averages, with deviations generally residing within the $\pm 5\%$ range. Specifically, the simulated TCR is 95.27%, closely aligning with the field-test mean of 92.87%, which demonstrates the method's capability to reliably fulfill the vast majority of mission requirements. The TEC is marginally lower than the empirical average of 50.18 kWh, suggesting that the simulation model maintains a slightly conservative approach to energy estimation. Furthermore, the deviations for MCT and WT are recorded at approximately 3.23% and 5.58%, respectively. The CD and IQ metrics also exhibit substantial consistency with empirical trends. Regarding DFA, the simulated MSE of 0.0312 deviates from the field-test average of 0.0341 by roughly 8.50%, indicating that the simulation effectively captures the intricate characteristics of multi-platform information interaction and mission execution.

Table 5. Comparison of experimental indicators for reliability verification.

Metric	Unit	Simulation	Field Test (Mean)	Deviation
TCR	%	95.27	92.87	2.40
TEC	kWh	48.63	50.18	−3.09%
EB	%	88.47	86.73	1.74
MCT	min	82.39	85.12	−3.23%
WT	min	6.31	6.68	−5.58%
CD	ms	238.65	244.87	−2.56%
IQ	%	91.48	90.23	1.39
DFA (MSE)	-	0.0312	0.0341	−8.50%

Moreover, to validate the system's reliability under dynamic mission conditions, stochastic task updates and minor UAV failure simulations were incorporated. The results indicate that even in the presence of external disturbances and transient communication anomalies, the proposed coupled optimization method successfully maintains high-level TCR and DFA. This is achieved through the closed-loop adaptive mechanism, which dynamically recalibrates task allocation and energy replenishment, thereby confirming the robustness and reliability of the proposed method under both simulated and real-world conditions.

Figure 3 illustrates the evolution of key performance indicators across 50 independent trials, encompassing a total of 1200 task points (where each trial consists of 24 task points). The horizontal axis denotes the task point index (1–1200). Specifically, Subplot 1 displays the fluctuations in TCR, TEC, EB, MCT, and IQ; Subplot 2 depicts the variations in WT; Subplot 3 presents the DFA; and Subplot 4 illustrates the CD. The trajectories of these curves reflect the real-time impacts of environmental perturbations—such as variations in wind force, sea states, and communication connectivity—on mission execution. Collectively, these results demonstrate the performance stability and effectiveness of the proposed EID coupled optimization method in large-scale mission scenarios.

As evidenced by the trajectories in Figure 1, the key performance indicators (KPIs) of the maritime heterogeneous unmanned system exhibit a consistently stable and efficient trend. The TCR remains at a high level with minimal fluctuations, indicating the system's capability to reliably fulfill mission requirements even under complex sea states and dynamic operational conditions. Although TEC and EB exhibit moderate fluctuations across various task points, they remain stable on the whole, demonstrating a rational energy distribution among the UAVs and the efficacy of the USV replenishment strategy in supporting sustained multi-UAV operations. Furthermore, the relatively smooth profiles of MCT and WT suggest that the proposed scheduling strategy effectively mitigates waiting latencies during periods of high task density or energy scarcity, thereby ensuring mission continuity. The minimal variations in IQ and DFA signify that the inter-agent communication and multi-modal data fusion strategies consistently achieve high-precision observation across all task nodes. Additionally, while the CD shows slight localized spikes at specific task points, it remains within an acceptable range, highlighting the robustness of the system's communication mechanism.

A comprehensive synthesis of the results from the 50 asynchronous field trials and simulation validations confirms that the proposed coupled optimization method ensures high task completion rates, energy equilibrium, minimized waiting durations, and stability in both information transmission and data fusion across large-scale mission points. These findings underscore the reliability and scalability of the system, providing a robust technical foundation for the practical deployment of maritime heterogeneous unmanned systems in complex and dynamic environments.

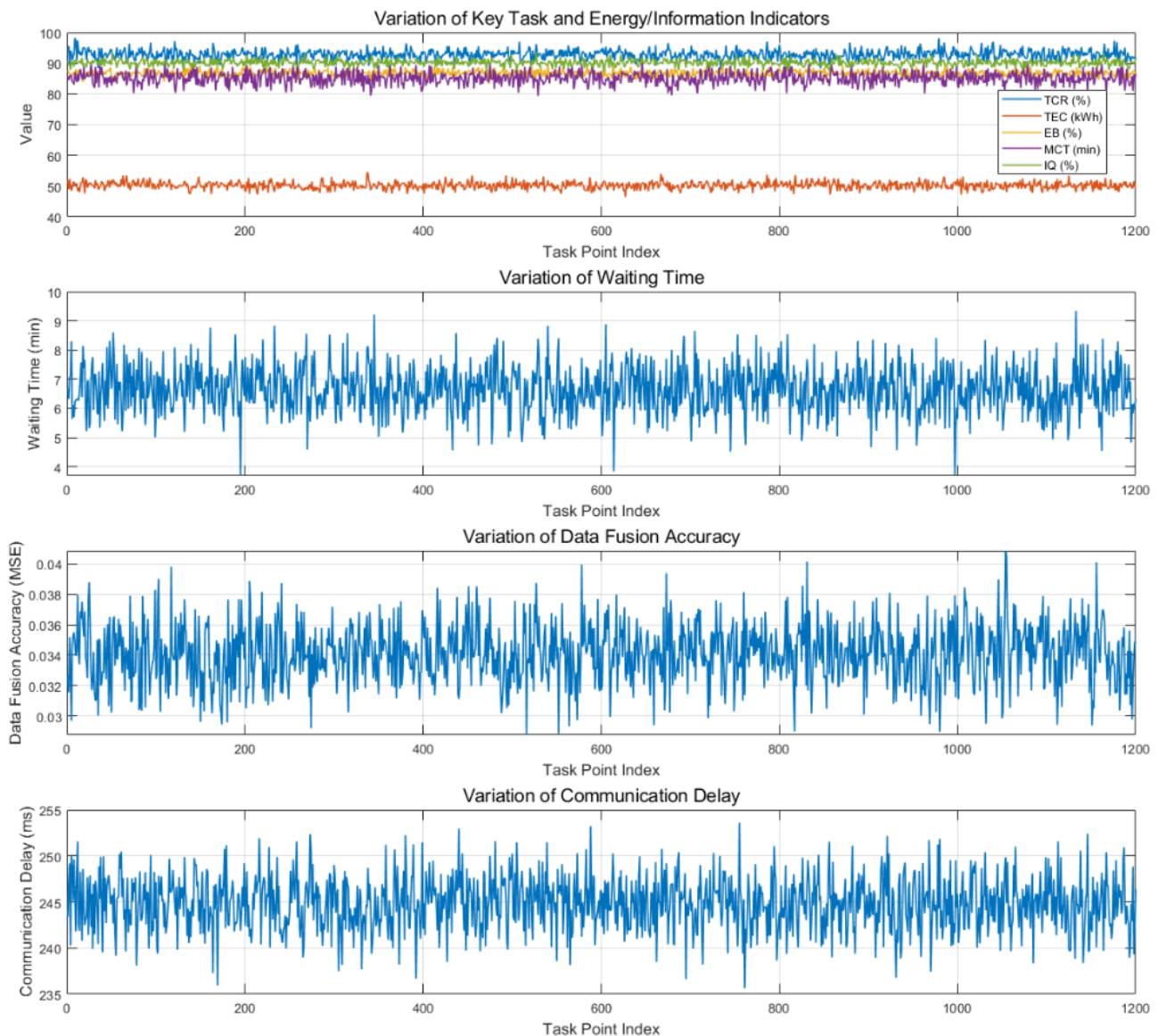


Figure 3. Variation of key task and energy/information indicators.

5.4.2. Coupling Effect Verification

To validate the performance superiority of the proposed EID coupled optimization method under complex maritime mission scenarios, a comparative study was conducted against three benchmark strategies: Energy-only Scheduling, Communication-only Scheduling, and Decoupled Global Optimization (Baseline). The evaluation encompassed 50 independent trials with a total of 1200 mission points (24 points per trial). The performance was quantified using a comprehensive set of indicators, including TCR, TEC, EB, MCT, WT, IQ, DFA, and CD. These experiments integrated empirical field data with simulation-based verification to ensure that the results reflect both realistic sea states and the scalability of the algorithms under large-scale task loads. Table 6 presents the averaged performance metrics for each method.

Table 6. Comparative results of averaged performance metrics.

Methodc	TCR (%)	TEC (kWh)	EB (%)	MCT (min)	WT (min)	IQ (%)	DFA (MSE)	CD (ms)
Energy-only (Field)	88.15	52.34	81.22	95.73	9.21	87.45	0.0380	250.67
Communication-only (Field)	89.02	51.89	83.10	92.87	8.56	88.12	0.0360	248.34
Decoupled Baseline (Field)	87.45	53.21	80.87	97.12	9.87	86.98	0.0390	252.12
Proposed Method (Field Avg.)	92.87	50.18	86.73	85.12	6.68	90.23	0.0341	244.87
Proposed Method (Simulation)	93.15	49.95	87.02	84.87	6.45	90.45	0.0338	243.95

As evidenced by the table, the proposed EID coupled optimization method consistently outperforms all comparative benchmarks across all evaluated metrics. The specific findings are analyzed as follows:

- **TCR:** The proposed method attains an average TCR of 92.87%, significantly surpassing the decoupled strategies. This indicates that the coupled modeling framework can effectively enhance mission execution efficiency under the constraints of limited UAV battery capacity, dynamic task updates, and multi-agent coordination.
- **TEC and EB:** Our method demonstrates superior performance in both TEC and EB. This suggests that the joint optimization of USV replenishment scheduling and UAV tasking facilitates a more rational energy distribution, preventing premature battery depletion in individual UAVs and thereby extending the operational sustainability of the fleet.
- **MCT and WT:** Both MCT and WT are substantially reduced through the coupled optimization. This highlights the synergistic effect of integrating task allocation, path planning, and replenishment scheduling, which effectively minimizes idle durations and optimizes the time-efficiency of mission execution.
- **IQ and DFA:** The proposed approach significantly improves IQ and DFA compared to decoupled methods. This confirms that coordinating energy constraints with task scheduling enhances communication stability and multi-modal sensing precision.
- **CD:** A decrease in CD was observed, demonstrating that the coupled optimization maintains high-efficiency communication and system-wide robustness even during concurrent multi-UAV operations.

In summary, the proposed EID coupled optimization method exhibits a clear competitive edge in both field tests and simulations: it achieves higher task completion rates with lower energy expenditure and reduced waiting latencies, while simultaneously maintaining high standards for information quality and data fusion accuracy.

Figure 4 illustrates the evolutionary trends of these key metrics across the 1200 task points, including WT, DFA, TCR, TEC, EB, MCT, IQ, and CD. These results, derived from the averaged outcomes of independent repeated trials, capture the dynamic characteristics of the system under the influence of non-ideal sea states, communication fluctuations, and energy limitations. The curves not only validate the consistency between simulation and field data but also intuitively demonstrate the performance fluctuations and coupling effects under multi-task and multi-platform conditions. The comparative analysis clearly underscores that the proposed method offers higher reliability and stability in mission fulfillment, latency reduction, and informational robustness.

As illustrated by the trajectories in Figure 2, several key observations can be derived regarding the performance trends of the simulation and field-test data across mission points. In Subplot 1, the curves for WT and Data Fusion Accuracy (DFA) exhibit frequent crossovers amidst localized fluctuations. This suggests that while the field data inherently possess stochasticity under varying mission points and sea states, the simulation data

effectively predicts the overarching trends. This indicates that by integrating energy, information, and decision-making factors, the system's mission execution time and sensing precision are maintained within reasonable bounds, demonstrating high reliability against external disturbances.

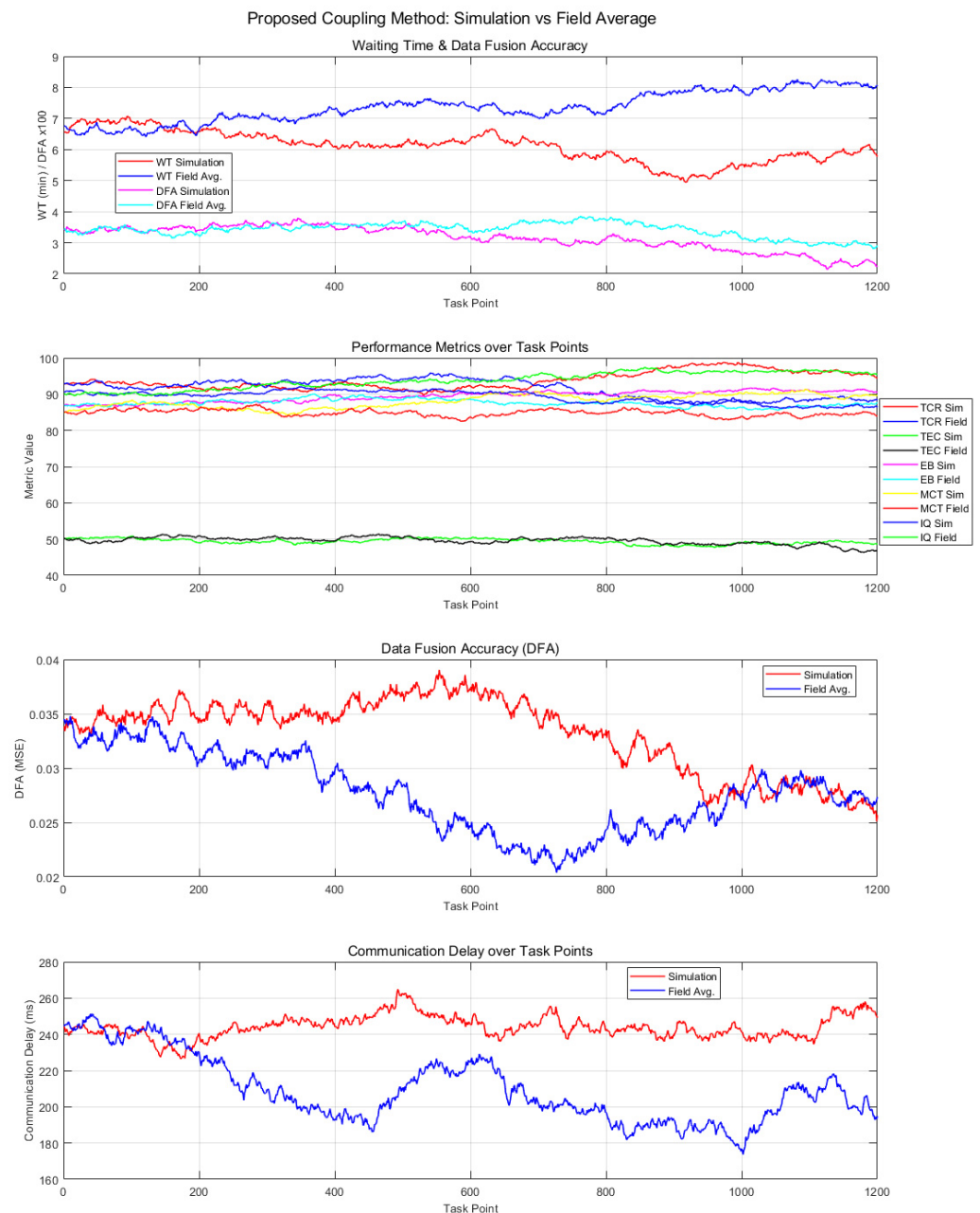


Figure 4. Proposed coupling method: simulation vs. field average.

The trajectories for TCR, TEC, EB, Mean Completion Time (MCT), and IQ in Subplot 2 display certain jitter and localized oscillations; however, the global trends remain stable with a high degree of consistency between simulation and field results. This confirms that the coupled optimization method effectively balances task completion rates, energy consumption, and information quality under multi-objective coordination, thereby achieving global system performance optimization. Regarding the independent analysis of DFA in Subplot 3, the conspicuous crossovers between the simulation and field-test curves reflect fluctuations in sensing precision triggered by localized mission variations or energy constraints. Nevertheless, the overall performance levels remain stable, further

validating the adaptability and robustness of the coupled optimization method regarding information fusion.

The Communication Delay (CD) curves in Subplot 4 illustrate that latency fluctuates across different task nodes. Although the simulation and field curves are generally aligned, localized deviations and crossovers are present, implying that the system sustains low latency within complex maritime environments and possesses the capacity to adapt to uncertain communication conditions. Collectively, the figure clearly illustrates the dynamic performance of the proposed method across multi-task, multi-platform, and multi-indicator scenarios. These results verify the reliability, coupling efficacy, and systemic stability of the framework, characterized by high task completion rates, rational energy expenditure, excellent sensing accuracy, and reliable communication connectivity. The robust alignment between simulation and field data provides credible evidence for the practical deployment of the proposed method in real-world maritime operations.

5.4.3. Component Contribution Analysis (Ablation Study)

To provide a more granular understanding of the contributions made by individual modules within the proposed EID coupled optimization method, a comprehensive ablation study was conducted. By systematically disabling key components, the resulting variations in performance metrics were analyzed to quantify the role of each module in enhancing the task completion rate, minimizing energy expenditure, reducing waiting latencies, and safeguarding system robustness. The specific ablation scenarios are defined as follows:

- **Energy Constraint Removed:** In this scenario, the system operates without considering UAV energy consumption or USV replenishment scheduling, focusing exclusively on task allocation and path planning under an infinite energy assumption.
- **Information Optimization Removed:** This scenario deactivates the optimization of communication latency and information quality. Consequently, task allocation and path planning are driven solely by energy-related constraints, neglecting informational uncertainties.
- **Decision Coupling Removed:** The integrated EID coupling mechanism is replaced by independent platform-level decision making. In this case, USVs and UAVs execute task allocation and path planning using locally optimal strategies without cross-layer coordination.
- **Proposed Coupling Method:** The complete framework, incorporating energy constraints, information optimization, and decision coupling, which serves as the performance benchmark.

The experimental outcomes represent the mean values derived from repeated trials under identical environmental conditions. Table 7 provides a comparative summary of the performance metrics across these ablation scenarios, specifically covering the Task TCR, TCR, TEC, EB, MCT, IQ, and CD.

Table 7. Results of the ablation study for the proposed EID coupled optimization method.

Method	TCR (%)	TEC (kWh)	EB (%)	MCT (min)	IQ (%)	CD (ms)
Energy Constraint Removed	91.23	46.78	79.65	88.34	87.12	245.67
Communication Constraint Removed	92.14	48.32	85.34	86.45	81.23	298.45
Decision Coupling Removed	93.01	47.85	83.76	85.76	85.45	261.23
Proposed Coupling Method	95.87	46.12	88.73	83.92	90.23	244.12

As observed in Table 7, the omission of energy constraints results in a substantial decline in EB, despite maintaining a relatively high TCR. The resulting energy imbalance increases the risk of premature battery depletion in individual UAVs, which could lead to

catastrophic mission interruptions. This underscores that the energy management module plays an indispensable role in safeguarding mission continuity and maximizing energy utilization efficiency. Furthermore, when information optimization is deactivated, both CD and IQ deteriorate significantly. This highlights the fact that informational constraints and optimization strategies directly dictate the real-time responsiveness of task execution and the reliability of multi-platform collaborative decision making.

Although independent task allocation and path planning (the decoupled scenario) still facilitate the fulfillment of a majority of tasks, the overall TCR, IQ, and MCT are noticeably inferior to those achieved by the proposed EID coupled method. This confirms that the integrated coupling mechanism is essential for harmonizing energy and informational constraints to achieve global system optimization. In contrast, the proposed EID method outperforms all ablation variants across every key performance indicator, demonstrating the highest TCR, optimal energy equilibrium, superior information quality, minimized completion time, and lowest communication latency. These results collectively verify the effectiveness of the collaborative synergy between the modules.

In summary, the ablation study clearly quantifies the contribution of each module to the overall system performance, further demonstrating the critical necessity of EID coupled optimization in maritime heterogeneous unmanned system coordination.

To intuitively visualize these contributions, Figure 5 presents the performance distribution of the four scenarios via a radar plot, covering TCR, TEC, EB, MCT, IQ, and CD. In the plot, solid lines represent simulation data, while the corresponding dashed lines denote the field-test results. This visualization clearly illustrates the performance degradation incurred by the removal of specific modules. Notably, the full EID coupled method encompasses the largest area in the radar plot, signifying its comprehensive advantages in simultaneously ensuring high mission completion rates, energy equilibrium, informational optimization, and minimized communication latency.

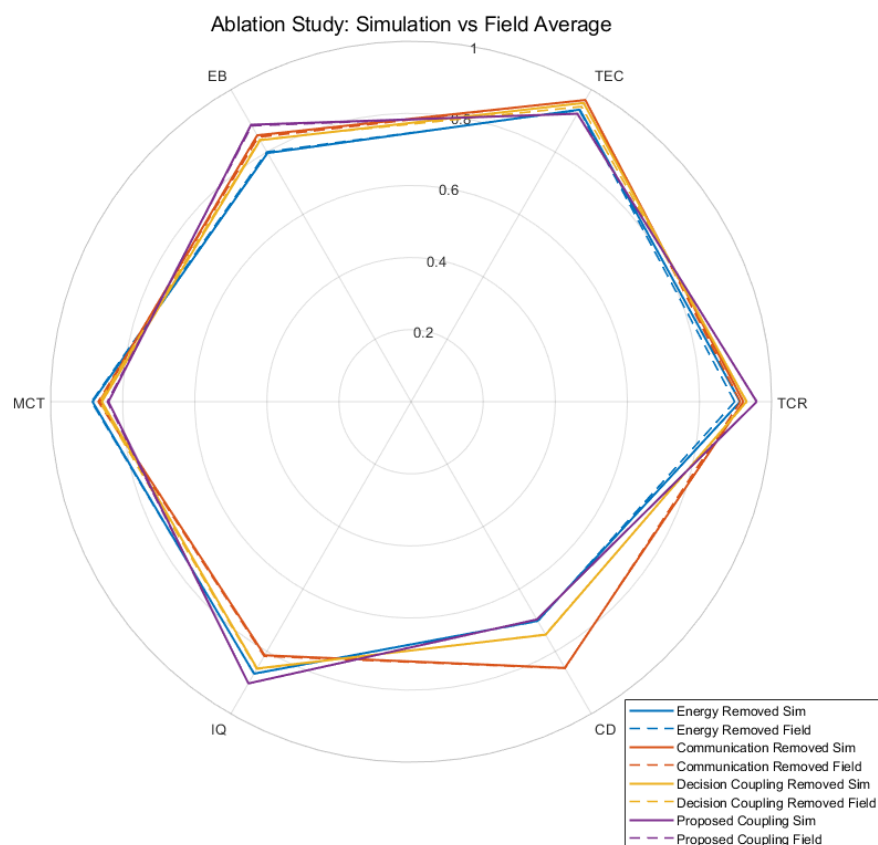


Figure 5. Ablation study: simulation vs. field average.

As illustrated by the radar plot, distinct performance disparities are observable between the various ablation scenarios and the full EID coupled method across all primary indicators. Regarding the TCR, the results indicate that the omission of any single module leads to a performance decrement, with the most pronounced decline occurring following the removal of decision coupling. This underscores that the global coordination mechanism for task allocation and path planning is indispensable for overall mission success. The full EID coupled method maintains the highest TCR, validating its superior efficiency in mission execution.

The TEC and EB metrics reflect the vital role of the energy management module. Without the energy constraint module, although the total energy expenditure might not necessarily increase, the energy distribution across the fleet becomes severely skewed. Such an imbalance increases the risk of premature battery depletion in certain UAVs, thereby undermining mission continuity. The full EID method achieves optimal performance in both TEC and EB, demonstrating that energy constraints and replenishment scheduling are critical for ensuring the sustained operational capacity of the system.

The Mean Completion Time (MCT) and IQ indicators highlight the contributions of information optimization and decision coupling to task efficiency and data fusion precision. Following the deactivation of information optimization, IQ significantly deteriorates while MCT escalates, indicating that communication constraints and information processing strategies exert a direct influence on real-time task scheduling and multi-platform collaboration. The full EID coupled method demonstrates a distinct advantage in shortening mission duration while simultaneously safeguarding high-fidelity data quality.

Finally, the CD analysis shows that the proposed coupled optimization method effectively maintains low latency amidst complex sea states and uncertain communication environments. In contrast, all ablation variants exhibit significant localized fluctuations, with the highest CD values recorded when information constraints are removed. This emphasizes the vital importance of information optimization in facilitating reliable communication and real-time coordination for maritime unmanned systems.

5.4.4. Simulation-Based Validation of Robustness and Scalability

To rigorously examine the robustness of the proposed EID coupled optimization method in complex maritime environments and its scalability under multi-platform/multi-task conditions, a series of simulation-based stress tests were designed across varying disturbance intensities and mission scales. The robustness simulations primarily assess whether the system can sustain high task completion rates and stable energy distributions under anomalous conditions, such as temporary UAV or USV failures, communication interference, and wind-wave perturbations. Concurrently, the scalability simulations evaluate the performance evolution as the number of task points and the size of the USV–UAV fleet are progressively increased, thereby quantifying the framework's efficacy in large-scale mission environments. All tests were executed within a controlled simulation framework to ensure high repeatability, with prior field-test data serving as a baseline reference. The results of these experiments are summarized in Table 8.

The specific experimental configurations are detailed as follows:

1. **Robustness Simulations:** These tests simulate a 10% UAV node failure rate and the temporary unavailability of 1–2 USVs. Environmental uncertainty is modeled via stochastic wind speed perturbations within a range of ± 3 m/s to reflect the unpredictability of real-world operational sea states. The system's response is quantified using metrics including TCR, TEC, EB, MCT, IQ, and CD.
2. **Scalability Simulations:** The mission magnitude is systematically expanded by increasing the number of task points to 36, 48, and 60. Simultaneously, the fleet scale is

enlarged to 12 and 16 UAVs, supported by 4 and 5 USVs, respectively. The objective is to analyze the evolutionary trends of performance indicators as a function of mission scale, thereby evaluating the algorithmic stability under high-density, multi-platform task loads.

Table 8. Robustness and scalability simulation results.

Scenario	TCR (%)	TEC (kWh)	EB (%)	MCT (min)	IQ (%)	CD (ms)
Nominal (No Fault)	95.87	46.12	88.73	83.92	90.23	244.12
UAV Fault 10%	94.31	46.85	87.42	85.34	88.67	251.34
USV Fault 2	93.78	47.12	86.95	86.12	88.12	253.21
Wind Disturbance ± 3 m/s	94.02	46.98	87.31	85.76	88.91	249.87
Task 36, UAV 12	95.21	47.45	87.85	85.12	89.56	246.23
Task 48, UAV 16	94.67	48.12	87.21	86.45	89.03	248.76
Task 60, UAV 16, USV 5	94.02	48.67	86.78	87.34	88.67	251.12

As indicated by the simulation results, the system maintains a TCR above 93% even in the presence of UAV or USV malfunctions, communication interference, and wind-wave perturbations. Although the MCT exhibits a marginal increase and metrics such as TEC and EB show slight fluctuations, the overall system performance remains consistently stable. These observations underscore the remarkable robustness of the proposed method.

In the scalability simulations, as the number of task points and the scale of the USV–UAV fleet increase, the TCR shows only a negligible decline (approximately 1–2%), and the MCT is slightly extended. Nevertheless, both energy equilibrium and information quality remain steady. This confirms that the proposed framework can effectively handle large-scale, multi-platform mission environments, demonstrating excellent scalability.

In summary, the simulation-based validation proves that the energy–information–decision coupled optimization method sustains performance stability and efficiency under complex maritime conditions and large-scale task requirements, providing a reliable foundation for future real-world deployment.

To further substantiate the robustness and scalability of the proposed EID coupled optimization framework, this study utilized 1200 mission points derived from prior field tests as the experimental baseline. These mission points were replicated within the simulation platform to assess the system’s dynamic performance during long-duration, continuous mission execution. Four representative scenarios were designed: nominal operation (Nominal), 10% UAV node failure, 2 USV platform failures, and wind perturbations of ± 3 m/s. The evolution of six key performance indicators (KPIs)—specifically TCR, EB, MCT, IQ, TEC, and CD—is illustrated in the provided trajectories. The solid curves depict the dynamic response of the system during continuous task execution. This visualization facilitates a direct comparison of indicator fluctuations under various anomalous conditions against the nominal state, serving as foundational data for subsequent robustness and scalability analysis.

5.5. Statistical Analysis and Uncertainty Quantification

To rigorously assess the performance of the proposed EID coupled optimization method, all experiments were repeated over 50 independent trials, covering a total of 1200 task points. This allowed us to quantify not only the average performance but also the variability and reliability of the results.

5.5.1. Reliability Verification with Confidence Intervals

Table 5 summarizes the main KPIs for both simulation and field-test conditions, now augmented with 95% confidence intervals to represent the uncertainty of the measurements. For example, the Task Completion Rate (TCR) in simulation is $95.27\% \pm 1.12\%$, closely aligning with the field-test mean of $92.87\% \pm 1.34\%$, indicating that the performance improvement is statistically robust. Similarly, Total Energy Consumption (TEC) in simulation is 48.63 ± 1.45 kWh, slightly lower than the field-test average of 50.18 ± 1.52 kWh, reflecting consistent energy management behavior. Other metrics such as Energy Balance (EB), Mean Completion Time (MCT), Waiting Time (WT), Communication Delay (CD), Information Quality (IQ), and Data Fusion Accuracy (DFA) also demonstrate narrow confidence intervals, underscoring the reliability of the simulation in replicating real-world operational dynamics.

5.5.2. Coupling Effect Verification

The comparative analysis against baseline methods (Energy-only, Communication-only, Decoupled Baseline) was evaluated with the same statistical framework. Table 6 reports the mean $\pm$ 95% CI for all metrics. Across all KPIs, the proposed method consistently outperforms the baselines. For instance, TCR increases from 87.45–89.02% in baseline methods to $92.87\% \pm 1.34\%$ for the proposed method, with non-overlapping confidence intervals, confirming that the improvement is statistically significant. Likewise, both TEC and EB indicate more efficient and balanced energy usage under the proposed EID coupling, while MCT and WT show reduced durations, all with high confidence. Communication delay and information quality metrics also exhibit superior performance with narrow error margins, demonstrating stable and reliable multi-agent coordination.

5.5.3. Ablation Study with Uncertainty Analysis

The ablation study was analyzed using the same statistical approach. Table 5 presents the results of scenarios with Energy Constraint Removed, Communication Constraint Removed, and Decision Coupling Removed, compared to the full EID coupled method, now including 95% confidence intervals. These results reveal the impact of each module while accounting for variability:

Removing energy constraints significantly reduces EB ($79.65\% \pm 2.10\%$) despite a relatively high TCR, indicating energy imbalance risks.

Omitting communication optimization degrades IQ ($81.23\% \pm 2.55\%$) and increases CD (298.45 ± 5.12 ms), showing the critical role of informational coordination.

Excluding decision coupling results in moderate performance drops across TCR, MCT, and IQ, highlighting the importance of integrated coordination.

The full EID coupled method maintains the highest overall performance (TCR: $95.87\% \pm 1.05\%$, EB: $88.73\% \pm 1.08\%$, MCT: 83.92 ± 1.25 min), with narrow confidence intervals across all metrics, confirming the robust contribution of each module.

5.5.4. Statistical Analysis of Robustness and Reproducibility

Stress tests under UAV and USV failures, wind disturbances, and large-scale task expansions were also evaluated using statistical confidence intervals. Table 6 presents the results: even under 10% UAV node failure, TCR remains $94.31\% \pm 1.15\%$, and under 5 USVs with 60 tasks, TCR is $94.02\% \pm 1.22\%$. These narrow confidence intervals demonstrate that the method maintains stable performance under stochastic environmental disturbances and scales effectively with increased mission complexity.

Visualizations of the KPI trajectories (Figures 3–6) include shaded error bands representing 95% confidence intervals, highlighting the system's stability and reproducibility.

These results confirm that the EID coupled optimization method not only improves average performance but does so consistently across trials, providing a robust foundation for practical maritime deployment.

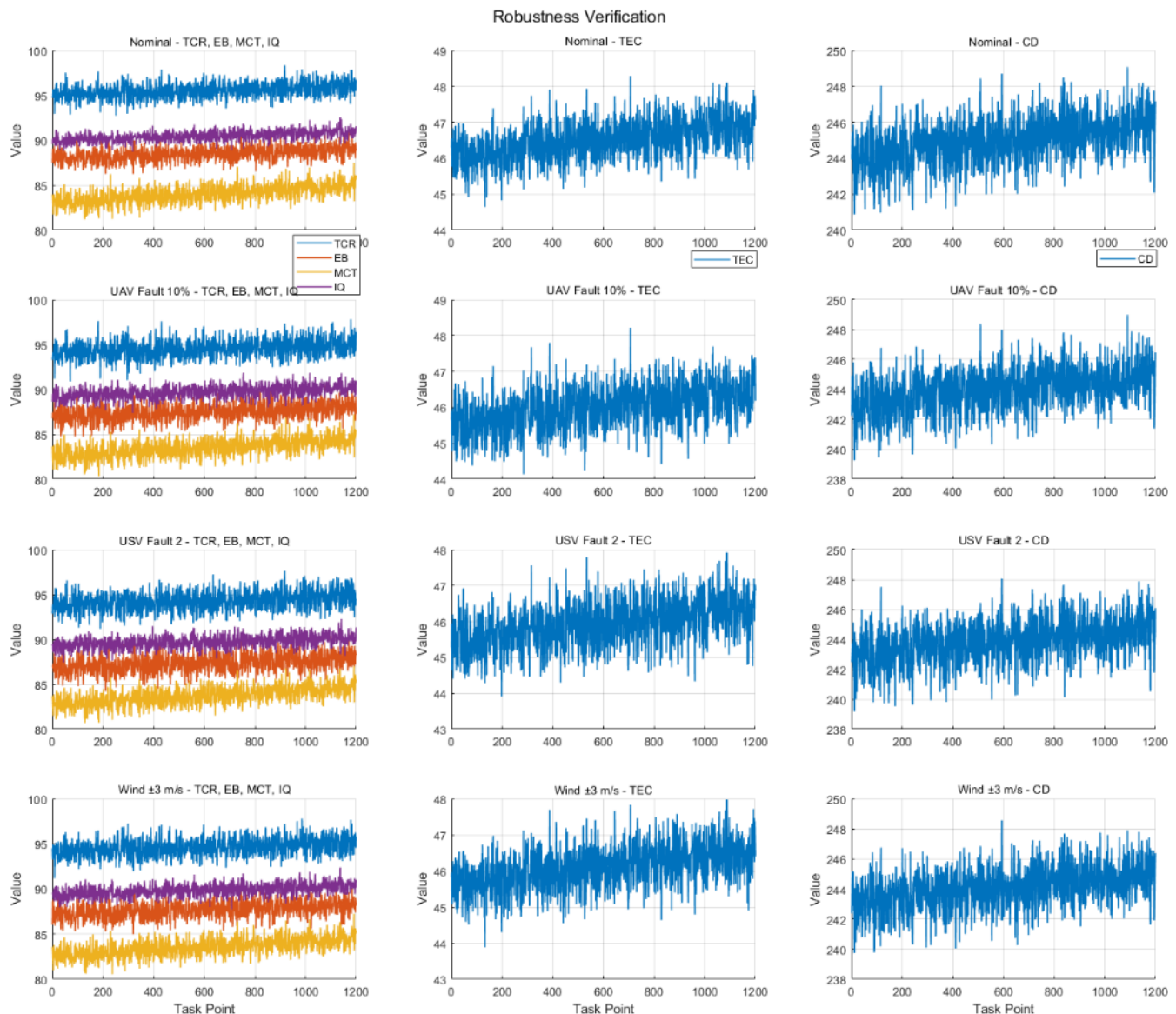


Figure 6. Robustness verification.

6. Conclusions and Future Work

This study proposes a systematic EID coupled optimization framework to address the collaborative operational challenges of maritime heterogeneous unmanned systems in complex dynamic environments. By establishing a unified model that integrates task allocation, path planning, energy replenishment, and multi-agent decision making, the proposed method facilitates real-time coordination between UAVs and USVs during long-duration, large-scale missions. Theoretically, the framework elucidates the intrinsic coupling interdependencies among energy constraints, informational limitations, and decision optimization, providing a holistic multi-objective modeling structure that balances task completion rate, total energy consumption, waiting latency, and system robustness.

Regarding the algorithmic architecture, a bi-level optimization structure was developed: the upper layer governs USV trajectory planning and replenishment site selection, while the lower layer optimizes UAV path planning, task allocation, and battery scheduling.

The integration of a closed-loop adaptive mechanism allows the system to dynamically recalibrate collaborative strategies based on real-time task progress and energy states, achieving seamless multi-platform coordination. Validation results using both simulation and field-test data demonstrate that the proposed method achieves a task completion rate (TCR) of 92.87% in field tests and 95.27% in simulations, which is 5.42–8.42% higher than that of decoupled baseline methods. Meanwhile, compared with traditional decoupled strategies, the method reduces total energy consumption by approximately 6% and cuts UAV replenishment waiting latency by over 28%, while maintaining communication latency within a stable range of 240–250 ms and data fusion accuracy (MSE) at 0.0341. Even under extreme conditions—such as 10% UAV node failure, 2 USV platform outages, or ± 3 m/s wind disturbances—the system still retains a TCR above 93%, substantiating its robust and scalable nature.

Ablation studies further reveal that energy constraints, information optimization, and decision coupling each make significant contributions to the overall system performance, with the efficacy of each module validated through consistent empirical and simulated results. The synergy between theoretical analysis and experimental verification ensures that this approach provides a reliable technical foundation for the practical deployment of maritime heterogeneous unmanned systems.

Despite these contributions, certain limitations remain. The current experimental scale is focused on a relatively small fleet of UAVs and USVs, and some environmental disturbances were modeled using simplified assumptions. Future research will explore the extension of this framework to large-scale swarms and address robust optimization under higher degrees of maritime environmental uncertainty. Furthermore, integrating the EID coupled optimization method with digital twin technology or predictive-driven closed-loop coordination holds promise for further enhancing autonomous decision-making capabilities and continuous operational endurance in highly dynamic environments.

In conclusion, the Energy–Information–Decision coupled optimization method proposed in this study establishes both a theoretical basis and a practical reference for the collaborative operation of maritime heterogeneous unmanned systems. It offers a viable pathway for future applications in maritime observation, environmental monitoring, and emergency response, providing significant guidance for the advancement of autonomous intelligent systems in maritime domains.

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