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PHD PROGRAM IN STRATEGIC ENGINEERING

**Autonomous Systems for Industrial and Marine Infrastructure
Inspection and Protection**

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Abstract

This Thesis focuses on the strategic engineering and application of AI-driven modeling and simulation of autonomous systems for the inspection and protection of critical marine and industrial infrastructures. The study includes multiple autonomous technologies including unmanned aerial vehicles (UAVs), unmanned underwater vehicles (UUVs), and surface vessels such as SWATH USVs to enhance inspection efficiency, reduce human risk, and provide real-time, high-quality inspection and survey. A key feature is the development of intelligent agents capable of autonomous decision-making, dynamic adaptation, and coordination across multi-domains: air, surface, underwater, seabed, space, and cyberspace in all scenarios. The research studies also the utilization of extended reality (XR) technologies to boost immersivity and interactivity of the systems in order to improve understanding of complex multidomain scenarios. Indeed, in addition to the above mentioned traditional and innovative physical assets, the study addresses their projections and interactions in the cyberspace, which is essential to analyze vulnerabilities such as communication disruptions, system interferences and even swarm attacks. In fact, deliberate and accidental disruptive actions becoming more frequent which makes this study particularly relevant in the modern context. In this setting, a proposed applied scenario demonstrates the coordinated deployment of fleets of multidomain autonomous systems for offshore inspection, maintenance, monitoring, and protection, showcasing complex multi-robot operations under challenging conditions. This work contributes to the advancement of autonomous, AI-enhanced solutions for the resilient management and protection of critical infrastructures, emphasizing adaptive, multi-domain strategic engineering principles.

Keywords: Autonomous systems, AI-driven modeling, simulation, critical infrastructure protection, unmanned aerial vehicles, unmanned underwater vehicles, SWATH USVs, multi-domain operations, Human-AI synergy, extended reality, maritime security, cyber- physical systems.

Abstract: Italiano

Questa tesi si concentra sull'ingegneria strategica e sull'applicazione di modelli e simulazioni basati sull'intelligenza artificiale di sistemi autonomi per l'ispezione e la protezione di infrastrutture marine e industriali critiche. Lo studio include diverse tecnologie autonome, tra cui veicoli aerei senza pilota (UAV), veicoli subacquei senza pilota (UUV) e imbarcazioni di superficie come gli USV SWATH, per migliorare l'efficienza delle ispezioni, ridurre il rischio per gli esseri umani e fornire ispezioni e rilievi in tempo reale e di alta qualità. Una caratteristica chiave è lo sviluppo di agenti intelligenti in grado di prendere decisioni in autonomia, adattarsi dinamicamente e coordinarsi in più domini: aria, superficie, immersione, fondali marini, spazio e cyberspazio, in tutti gli scenari. La ricerca studia anche l'utilizzo di tecnologie di realtà estesa (XR) per aumentare l'immersività e l'interattività dei sistemi al fine di migliorare la comprensione di scenari multidominio complessi. Infatti, oltre alle risorse fisiche tradizionali e innovative sopra menzionate, lo studio affronta le loro proiezioni e interazioni nel cyberspazio, essenziali per analizzare vulnerabilità come interruzioni delle comunicazioni, interferenze di sistema e persino attacchi a sciame. Infatti, le azioni distruttive deliberate e accidentali stanno diventando sempre più frequenti, il che rende questo studio particolarmente rilevante nel contesto moderno. In questo contesto, uno scenario applicato proposto dimostra l'implementazione coordinata di flotte di sistemi autonomi multidominio per l'ispezione, la manutenzione, il monitoraggio e la protezione offshore, illustrando complesse operazioni multi-robot in condizioni difficili. Questo lavoro contribuisce allo sviluppo di soluzioni autonome basate sull'intelligenza artificiale per la gestione resiliente e la protezione delle infrastrutture critiche, enfatizzando i principi di ingegneria strategica multidominio e adattiva.

Parole chiave: Sistemi autonomi, modellazione basata su AI, simulazione, protezione delle infrastrutture critiche, veicoli aerei senza pilota, veicoli subacquei senza pilota, USV SWATH, operazioni multidominio, sinergia Umano-AI, realtà estesa, sicurezza marittima, sistemi cyber-fisici.

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Chapter 1

INTRODUCTION

1.0.1 The Evolving Landscape of Critical Marine Infrastructure

Marine infrastructure has been seen as a group of installations that support offshore oil and gas maritime transport and fisheries. The marine infrastructure changed, over the years. For most of the 20th century marine infrastructure fit that picture. Marine infrastructure was made of static, heavy structures, fixed platforms, port facilities and shipping lanes. When a piece of infrastructure failed the failure was usually local. Marine infrastructure problems could hurt the economy. They rarely affected the whole modern society. This paradigm is no longer adequate. In the third decade of the 21st century, the ocean has become a foundational substrate for global connectivity and energy security. Critical marine infrastructure must now be understood as a system-of-systems (SoS) that integrates energy production, data connectivity, logistics, and environmental monitoring at a transnational scale (Bruzzone et al., 2021).

Ports and marine terminals are increasingly recognized as complex hubs where logistics, energy transition and safety are tightly coupled, with digital-twin studies such as ALACRES2 showing how LNG terminals, offshore energy links and microgrids reshape both operational efficiency and risk exposure (Bruzzone et al. 2011); (Bruzzone et al. 2021). Data-driven analyses of port accidents further reveal that improvements in safety correlate with investments in infrastructure modernization, training and monitoring capabilities, underlining the strategic centrality of these infrastructures.

The design, operation and the future changes of the assets now follow the imperatives of energy and resilience. The global demand, for energy and data pushes the building of wind farms deep sea oil and gas platforms and seabed resource gathering installations. This growth also brings a growing vulnerability. The assets are not isolated industrial parts; the assets are important strategic

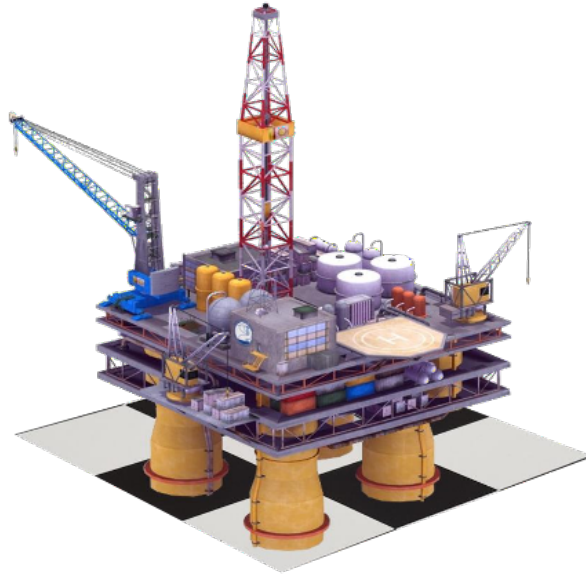


Figure 1.1: Virtual Representation of Oil Rig.

targets. The reality has forced the shift from a focus on protection to a much more complex need, for resilience. In the context of this research resilience is the capacity of an energy or data system to predict, absorb, adapt or recover from shocks and stresses quickly and effectively. The resilience guarantees that the consumers can always access the energy services. Here the resilience matters for life and the challenges are real. The shocks and stresses of the era are different in nature and complexity, from the shocks and stresses of the past. Today the marine infrastructure lattice includes renewable energy arrays. Offshore wind farms have grown from pilot projects into multi gigawatt installations far offshore. Offshore wind farms often have structures that join turbines, substations and export cables under hard weather conditions. I notice that digital connectivity vectors are another part. Subsea fiber optic cables carry intercontinental internet, financial and governmental traffic. Subsea fiber optic cables turn the seabed into the support, for the worldwide digital economy. Repurposed hydrocarbon assets and emerging uses reshape domains. Industry looks at legacy oil and gas infrastructure for repurposing. For example industry uses legacy oil and gas infrastructure for Carbon Capture, Utilization and Storage (CCUS). Carbon Capture, Utilization and Storage (CCUS) adds process requirements, new integrity requirements and new monitoring requirements, for aging structures. The aging

structures must meet those process requirements, integrity requirements and monitoring requirements. These systems are not isolated mechanical objects any more. The systems are now part of an infrastructure. Modern offshore platforms run on network systems, remote operation centers, edge computing units and dense sensor networks; subsea cables run on software-controlled repeaters and signal management; renewable farms run on real-time control and optimization. I notice that the evolution creates a vulnerability. The dual vulnerability means the systems face physical conditions and also face complex digital dependencies (Bruzzone et al. 2023).

1.0.2 Dual Vulnerability of Marine Socio-Technical Systems

In the domain we observed marine assets work in a harsh environment. Corrosion, water forces, sea growth, seabed erosion and ground instability are problems. Land structures can be repaired easily but offshore installations sit in a place that pushes back against people and work. In the domain marine assets face more automation and remote operation that add extra complexity. The supervisory control, sensor fusion and remote diagnostics need communication links and software controlled systems. Supervisory control, sensor fusion and remote diagnostics must stay reliable when there is noise, data loss or possible misuse or accidental interactions. The challenge is real. I also notice that as autonomy in shipping and offshore work grows we see that the two sides of risk are clearly noted in regulatory work, on Maritime Autonomous Surface Ships (MASS) (International Maritime Organization, 2021; (Orzechowski, 2024). This dual vulnerability means that physical degradation (e.g., scour at a monopile) and digital anomalies (e.g., erroneous sensor signals or communication loss) can interact and propagate across the system. Both must therefore be addressed jointly within a holistic resilience framework.

Harmonized port accident datasets demonstrate that incident patterns are driven by intertwined technical, organizational and human factors, confirming ports as socio-technical systems with shared risk signatures across countries (Bruzzone et al. 2011);(Bruzzone et al. 2021). At the same time, serious-game-based experiments in harbor environments highlight how cyber threats against digitalized processes and IoT/IIoT infrastructures are becoming as critical as physical hazards, reinforcing the notion of dual physical-cyber vulnerability.

Consider the case of a harbormaster in a bustling Asian port, where a last-minute equipment failure during routine docking operations forced rapid decision-making from the operator. The actions taken based largely on incomplete information led to a misjudgment that resulted in minor collisions and equipment

damage. The incident, later analyzed, highlighted how human factors can intricately interact with technical issues, embodying the complexities seen across various international ports. Such real-world scenarios emphasize the importance of coupling human experiences with data-driven insights to enhance the reliability and security of socio-technical systems.

1.0.3 The Limitations of Legacy Inspection Paradigms

Conventional inspection practices rely on surveys conducted with crewed vessels, divers, and tethered ROVs. However, these approaches do not align well with the scale and complexity of modern infrastructure systems. Legacy paradigms present several limitations, particularly in terms of data availability and temporal coverage. Sparse sampling restricts the depth of insight that inspections can provide. In many cases, inspections occur only once per year or every few years, which forces engineers to make integrity assessments based on data that may be several months old. This is problematic because degradation mechanisms such as scour or fatigue crack propagation can evolve rapidly following storms or operational changes. Operational risk and cost further constrain inspection frequency. Crewed inspections require vessels, specialized teams, and favorable weather windows, while also operating under strict safety constraints. The high cost associated with these operations significantly reduces how often inspections can realistically be carried out (Bruzzone, 2000). Data fragmentation also limits effective infrastructure management. Inspection logs, drone imagery, network data series, and environmental measurements are frequently stored in separate systems. The absence of integrated data frameworks makes it difficult to combine these heterogeneous datasets into a coherent operational picture. Without a unified data model or digital twin, situational awareness remains fragmented, which limits the ability to support long-term resilience planning (Bruzzone et al., 2023). These challenges highlight how many 21st-century cyber-physical infrastructures still rely on inspection paradigms developed for earlier operational contexts. Addressing these limitations requires a transition from time-based maintenance approaches toward continuous, model-driven, and data-rich resilience management.

Simulation studies on maritime interdiction and port crisis management further demonstrate that legacy schedule-based inspection systems and siloed information flows struggle to cope with dense traffic conditions, rapidly evolving threats, and cascading failures. Such limitations create operational blind spots in both surface and subsea infrastructure protection (Bruzzone et al., 2011; Bruzzone et al., 2021).

1.0.4 The Strategic Engineering Methodology

The Strategic Engineering Methodology Fixing the limits of monitoring and protection systems needs more than small improvements, in robotics or sensor technology. Today's marine infrastructures cover the air, the surface, the subsurface, the coastal, the space and the cyber areas. The marine infrastructures need a method that can show how the parts depend on each other can mix the data and can support flexible real-time decision making. Strategic Engineering links Modeling & Simulation (M&S) data analytics, Artificial Intelligence and digital twin technologies, in the closed-loop framework (Bruzzone et al. 2021); (Bruzzone et al. 2022).

Prior Strategic Engineering applications in marine security and pandemics combine a Situation Analyzer, interoperable simulation models and AI-based planners in a closed loop, continuously refining courses of action based on simulated and observed system responses (Bruzzone et al. 2011); (Bruzzone et al. 2021). These results motivate using the same paradigm here to structure data fusion, modeling and decision support for marine infrastructure inspection and protection.

Unlike traditional systems engineering, which typically focuses on optimizing static system designs against predefined requirements, Strategic Engineering explicitly models the environment as dynamic and uncertain, acknowledging that systems evolve over time and that decisions must continuously adapt to new information. This orientation is particularly relevant in marine domains where operational conditions, environmental stressors, and logistical constraints may shift rapidly, and where early detection of anomalies can substantially influence asset longevity, safety, and resilience.

1.1 Conceptual Pillars

Strategic Engineering rests on three linked pillars that support the system understanding and the better decision making. The first pillar, Modeling & Simulation (M&S) makes simulation a constant function across the life of infrastructure. I notice that simulation is not for design verification. Simulation becomes a tool for exploring scenarios, for planning operations and, for anticipating risks. The approach matches the research in maritime and port-operations research (MASSEI et al. 2013). The second pillar is Artificial Intelligence and Intelligent Agents (IAs). I see that Artificial Intelligence and Intelligent Agents (IAs) coordinate planning detect anomalies. Reconfigure missions across different autonomous systems. I also see that Artificial Intelligence and Intelligent Agents (IAs) are essential to manage UAVs, USVs, AUVs, sensor networks and digital

services in offshore areas. Artificial Intelligence and Intelligent Agents (IAs) let the system make decisions that follow the rules of each area and also think about the system. Finally, data analytics and digital twins form the third pillar by transforming a continuous influx of multi-domain sensor data into a coherent, dynamically updated representation of the physical system. This digital twin acts as the central reference point for comparing predicted and observed system behaviour, thereby supporting anomaly identification, model refinement, and strategic foresight (Bruzzone et al., 2023). Together, these pillars enable a structured yet adaptive methodology for managing the complexities of modern marine infrastructures.

1.1.1 Closed-Loop Control Architecture

From a theory view Strategic Engineering is a feedback system that always tries to keep the real world and the virtual model matching. I notice that Strategic Engineering works in four linked steps that build a system that learns and helps make decisions. The first step, called Heterogeneous Data Fusion (Observation) gathers data from health sensors, network systems, UAV imagery, USV radar, AUV sonar, environmental measurements and operational logs. The first step puts all that data together into a Common Operational Picture (COP). This integrated perspective allows stakeholders and intelligent agents to reason about the state of offshore assets with a level of spatial and temporal coherence that individual datasets cannot provide. I work with the phase, AI-driven simulation (Prediction) that uses digital twins and intelligent agents. AI-driven simulation (Prediction) runs faster than time simulations that predict how hazards, like scour, corrosion, hydrodynamic loading or cyber-physical degradation will develop. Techniques such as Monte Carlo analysis, agent-based modelling, and scenario exploration allow the system to evaluate a broad spectrum of possible futures, a capability highlighted in several works on simulation-based engineering by Bruzzone and colleagues (Bruzzone et al., 2021). Decision Augmentation (Prescription) forms the third phase, shifting from raw, high-volume data toward concise, actionable guidance. Instead of overwhelming operators with sensor readings or alarms, the system synthesizes information to recommend feasible courses of action retasking AUVs, scheduling re-inspections, reducing operational loading, or adjusting vessel trajectories while quantifying associated risks and trade-offs. The fourth phase, Adaptive Refinement (Learning), completes the feedback loop. Here, the system compares predicted behaviour with observed outcomes, using discrepancies to improve model fidelity and refine decision policies. Methods such as Bayesian updating, reinforcement learning, or statistical calibration help maintain the long-term accuracy and reliability of the digital twin, supporting the continuous evolution of operational strategies (Bruzzone et al., 2021).

1.1.2 The Autonomous Triad: Integration of UAVs, USVs, and AUVs

Integration of UAVs, USVs, and AUVs Because the offshore energy systems, subsea cable networks and port-related infrastructures have parts no single robotic asset can give full situational awareness or inspection coverage. The UAVs do aerial assessments but the UAVs have limited endurance and the UAVs are sensitive, to weather. The USVs provide duration missions and stable platforms for sensing and communication but the USVs lack reach beneath the surface by design. Using both the UAVs and the USVs can give coverage. AUVs deliver the detailed subsea inspection required for monitoring buried cables, pipelines, or seabed installations, yet operate under GPS-denied conditions with severe communication constraints (Fossen, 1994). To overcome these limitations, this research adopts a heterogeneous autonomous triad UAV + USV + AUV configured as a coordinated system-of-systems. Digital-twin testbeds of autonomous vehicles in heavy industrial environments show that carefully configured combinations of LIDAR, cameras and ultrasonic sensors can deliver robust human and obstacle detection even under dust, noise and challenging illumination. In port and terminal scenarios, interoperable simulators and XR-based serious games demonstrate that integrating such autonomous systems with human operators improves both situational awareness and safety during critical handling and emergency operations (Bruzzone et al. 2011);(Bruzzone et al. 2021).

At the centre of this triad is the Unmanned Surface Vehicle (USV), which functions as the operational nexus. Based on vehicle guidance and control principles, USV offers three services. The USV works as an energy hub, for UAVs and AUVs. The USV lets UAVs and AUVs recharge or swap batteries. The USV works as a communication relay. The USV translates low-bandwidth messages from underwater vehicles into high-bandwidth radio or satellite signals. The USV works as a navigation reference. The USV provides a GPS-stabilized platform that helps underwater vehicles locate themselves with Ultra-Short Baseline (USBL) or related acoustic systems (Fossen, 1994).

The integration of these roles allows the USV to maintain persistent offshore operations independent of continuous human intervention a capability emphasized in recent strategic engineering studies on autonomous marine assets (Bruzzone et al., 2022). UAVs in the triad fulfil the need for high-resolution, agile visual assessments of topside infrastructure, including blade inspection for offshore wind turbines, surface condition monitoring following storm events, or rapid confirmation of anomalies detected by subsea or surface platforms. Their

operational constraints limited battery life, weather dependence, and the need for safe launch and recovery underscore the importance of coordination with the USV. Autonomous Underwater Vehicles (AUVs) provide detailed subsea inspection capabilities including pipeline and cable tracking, scour monitoring at foundations, and inspection of subsea manifolds and connectors. Their autonomy is constrained by GPS denial, limited communication bandwidth, and complex underwater dynamics. These factors reinforce the importance of USVs as communication and localisation anchors, as well as the need for robust control strategies grounded in marine vehicle dynamics (Fossen, 1994). The triad therefore enables capabilities that no individual platform can provide, including multi-domain data fusion, redundancy across sensing modalities, and adaptive re-tasking of vehicles as environmental conditions change.

1.1.3 The Role of Autonomous Systems in Marine Infrastructure

Autonomous systems are now important tools for checking, watching and taking care of important sea structures. The wind farms out at sea grow larger underwater cables become denser and far away energy sites get more complex. The need for safe and detailed checking has risen. Autonomous systems can stay on the job for periods and can look at places that people, on boats and divers cannot reach. Autonomous systems can collect data without putting people at risk. The old crewed methods cannot keep up with the demand. Unmanned Aerial Vehicles (UAVs), Unmanned Surface Vehicles (USVs), and Autonomous Underwater Vehicles (AUVs) now form the backbone of modern inspection operations, supporting tasks such as structural-integrity assessment, anomaly detection, corrosion monitoring, seabed deformation analysis, and environmental data collection. In marine offshore operations, a careful distinction must be made between automated and autonomous systems. Automated platforms such as pre-programmed drones or piloted Remotely Operated Vehicles (ROVs) follow predefined routines or require constant operator input. Autonomous systems, by contrast, possess the capacity to sense environmental and asset conditions, decide on appropriate responses based on mission objectives, and act through real-time maneuvering and adaptive data collection. I see that the transition from automation to autonomy supports the ability of the inspection systems to work safely and efficiently in the changing hard marine environments. Even though there has been progress some limits still exist. UAV inspections often happen alone. Do not fully connect to the whole asset health or digital-twin models. USVs often work in single purpose jobs, often bathymetric mapping without better coordination, with subsea assets. AUVs, although highly capable,

remain costly to operate and are constrained by endurance, navigation drift, and mission-profile rigidity.

The regulatory landscape further reinforces the need for robust oversight: the International Maritime Organization’s MASS (Maritime Autonomous Surface Ship) framework emphasizes that, regardless of increasing autonomy levels, human supervision remains essential for safety, environmental protection, and operational responsibility (IMO, 2021; Orzechowski, 2024). These considerations collectively justify the need for a unified architectural approach in which autonomous systems, digital twins, and human supervisors function as an integrated decision-support ecosystem governed by strategic engineering principles. In the context of critical marine infrastructure, autonomous systems now support inspection and maintenance through structural integrity assessment, anomaly detection, and corrosion monitoring; hazard detection, including seabed deformation, free spans, or emergent features; and environmental monitoring through measurement of waves, currents, turbidity, and ecological parameters in and around infrastructure sites. We need to make a distinction, between automated systems and autonomous systems. Automated systems include the pre-programmed vehicles or ROVs that need pilots. Autonomous systems can sense the environment and the condition of assets. Autonomous systems decide on plans. Adapt their behaviour without a human telling them what to do. Autonomous systems act execute the required manoeuvres. Capture the data safely,. Despite significant progress, the current state of practice reveals limited integration of UAV inspections into holistic asset health models; USVs are often used in single-purpose roles (e.g., bathymetry) without deeper coordination with subsea assets; and there is high cost and limited flexibility of many AUV operations. I notice that the regulatory developments around MASS say that while autonomy grows human oversight stays central for safety security and environmental performance (International Maritime Organization, 2021; Orzechowski, 2024). I notice that the regulatory developments around MASS create a need, for an architecture that integrates systems and human supervisors through strategic engineering. The architecture should not treat systems and human supervisors as separate parts.

1.1.4 Foundations of Marine Vehicle Autonomy: Control and Guidance Theory

Autonomous marine vehicles (UAVs, USVs, and AUVs) rely on Guidance, Navigation, and Control (GNC) theory. I observe that marine autonomous systems follow the GNC pipeline to achieve trajectory guidance, navigation state estimation, and closed-loop control. Fossen’s book *Guidance and Control of Ocean*

Vehicles provides the core mathematical formalism for modeling marine vehicle motion, sensor fusion, and control allocation (Fossen, 1994). This framework forms the foundation for autonomous inspection and infrastructure monitoring systems. From my experience working with vehicles, I understand that marine vehicles operate in six degrees of freedom (surge, sway, heave, roll, pitch, and yaw). Their dynamics are strongly nonlinear due to hydrodynamic drag, added mass effects, non-uniform current profiles, wave-induced forces, actuator saturation, actuator faults, and shallow-water or structure-proximity effects. (Fossen, 1994) expresses the coupled rigid-body and fluid-interaction dynamics as:

$$M\dot{\nu} + C(\nu)\nu + D(\nu)\nu + g(\eta) = \tau$$

where η is the vehicle pose, ν is the body-fixed velocity vector, M is the combined inertia matrix (rigid + added mass), $C(\nu)$ represents the Coriolis and centripetal term, $D(\nu)$ denotes damping, $g(\eta)$ includes restoring forces, and τ is the vector of generalized control forces and moments. I observe that this formalism produces realistic behavior in simulation frameworks, particularly for USVs and AUVs navigating near offshore infrastructure, including turbine foundations and subsea cable routes.

Navigation challenges differ across domains. UAVs rely on GPS, IMU, magnetometers, and optical flow, but may drift under strong wind or poor lighting. USVs exhibit strong GPS observability but are affected by wave-induced motion and GNSS multipath interference near structures. AUVs cannot access GPS underwater and therefore depend on Doppler Velocity Log (DVL), acoustic localization methods such as Ultra-Short Baseline (USBL) or Long Baseline (LBL) beacons, and terrain-relative navigation (TRN).

The navigation filter typically follows a Kalman formalism. For nonlinear marine sensor models, many autonomy stacks favor the Unscented Kalman Filter (UKF) or Extended Kalman Filter (EKF). The filter fuses multi-sensor measurements into a full vehicle state estimate using an innovation update model:

$$\hat{x}(k+1) = f(\hat{x}_k, u_k) + K_k(z_k - h(\hat{x}_k))$$

where f is the process model representing vehicle dynamics, and h is the measurement model that represents onboard sensor observations.

The true autonomy requires tight integration between high-level decision making and low-level control loops. Marine autonomy architectures commonly follow a multi-layer hierarchy:

Mission Planning Layer: task scheduling, waypoint generation, and power or resource management.

Guidance Layer: path following, target tracking, and collision or obstacle avoidance.

Control Layer: thruster force control, orientation regulation, station keeping, and stabilization.

These layers enable heterogeneous autonomous agents to perform infrastructure inspection behaviors, such as traversing subsea cable routes, station keeping near structures, adapting survey patterns under turbidity or current shifts, and coordinating in multi-vehicle teams. This multi-layer autonomy hierarchy forms the foundation of the heterogeneous autonomous triad developed in this thesis.

1.1.5 IMO MASS Autonomy Levels: A Regulatory and Operational Framework

The International Maritime Organization (IMO) has established the first globally recognised framework for Maritime Autonomous Surface Ships (MASS). The IMO's Regulatory Scoping Exercise (RSE) defines four autonomy levels (IMO, 2021), each describing how human operators interact with autonomous systems.

Level 1: The ship uses automated processes and decision support, but humans are still responsible for navigation and operation. Digital systems help with monitoring and sending alerts.

Level 2: The ship is controlled remotely from an operations center, but crew members stay on board to step in if needed.

Level 3: The ship is operated entirely remotely with no crew on board, so it needs backup systems and safety measures.

Level 4: The ship is fully autonomous, making its own decisions and acting on them. Human oversight exists in principle, but not in real time.

These definitions clarify how autonomy, human oversight, and regulations are connected. Commercial inspection USVs and AUVs usually work at Level 3 or 4, depending on the mission. Offshore UAVs are often at Level 1 or 3, especially when remote operation centers are involved. Hybrid operations, like coordinating

UAVs, USVs, and AUVs, can span several autonomy levels and need strong supervision and clear human involvement. IMO MASS is important to this thesis for two reasons. First, it provides a marine regulatory framework, making sure the work follows non-military rules for autonomous ships. Second, it guides how supervisory systems, communication protocols, and safety features are designed in the inspection system. Recent studies (Orzechowski, 2024) show that MASS rules will strongly influence future offshore work, especially in remote supervision, communication standards, situational awareness, and human-machine interface design. These factors directly support the methods and design choices in this research, especially for XR interfaces and human oversight.

1.1.6 Integrating Control Theory with Strategic Engineering

Control theory manages the detailed behavior of vehicles, while Strategic Engineering handles the bigger picture needed for complex infrastructure monitoring. These two are connected through digital twins that link vehicle status and infrastructure health, intelligent agents that turn inspection goals into tasks, and real-time feedback loops that combine sensor data, simulations, and operator input.

This theory keeps vehicles safe and precise, MASS regulations make sure autonomy is responsible and supervised, and Strategic Engineering helps optimize inspection missions across the whole system. Together, these form the foundation of the operational approach in this thesis.

1.1.7 Implications for Marine Infrastructure Inspection

The integration of classic control theory, modern autonomy levels, and Strategic Engineering leads to several implications for Marine inspection operations. Autonomy is not a single capability but a layered system requiring both physical control and cognitive decision-making. Human oversight remains essential, not because autonomy is inadequate, but because safety standards require it under MASS regulatory frameworks. Digital twins and simulation tools must be tightly integrated with low-level control and high-level planning to maintain infrastructure resilience. The heterogeneous autonomous triad needs coordinated multi-layer autonomy that respects regulatory, environmental, and physical constraints. As marine infrastructure grows in scale, complexity, and criticality, these combined foundations become indispensable for safe, efficient, and resilient monitoring operations.

Virtual laboratories for port accidents and XR-based operator training indicate that embedding autonomous assets into inspection workflows enables continuous condition monitoring and richer validation of contingency plans than purely human-centric approaches. Strategic-Engineering simulations further show that coordinated human–autonomous operations, supported by digital twins and AI, are essential to maintain resilience against both routine degradation and rare high-impact events affecting critical marine infrastructures (Bruzzone et al. 2011) ; (Bruzzone et al. 2021).

1.2 Problem Statement

Although autonomous systems, digital twins, and advanced simulation tools offer significant promise for the inspection and monitoring of marine infrastructure, the offshore sector continues to face a critical gap between the theoretical potential of these technologies and their practical, real-world deployment. Much of this gap is attributed to the insufficient fidelity, integration, and realism of existing simulation environments, which limits the industry’s ability to validate autonomous behaviours before field deployment. Current tools tend to compartmentalise environmental layers, oversimplify physics, treat infrastructure as static, and provide operators with inadequate decision-support interfaces. This fragmentation makes it extremely difficult for engineers to design, test, and refine autonomous inspection missions with the confidence required for operations involving high-value and safety-critical marine assets.

A unified approach based on Strategic Engineering is needed. This approach should combine environmental physics, realistic robot behavior, dynamic infrastructure models, multi-sensor data, and human-focused visualization into one framework for resilience assessment (Bruzzone et al., 2021), (Bruzzone et al., 2023). The next sections explain the specific gaps that drive the methods used in this thesis.

1.2.1 Absence of Coupled Interactions

Real offshore inspection missions inherently involve tightly interlinked operations between aerial, surface, and subsea robotic systems. For instance, UAVs must often launch from and land on moving USVs a task requiring precise deck-motion prediction, wind compensation, and real-time control under wave-induced disturbances. Similarly, AUVs rely on surface vessels for acoustic localisation, because underwater vehicles cannot access GNSS and instead must depend on USBL/LBL systems mounted on USVs, which themselves are influenced by sea

state and vessel motion. At the same time, USVs act as critical communication bridges, relaying data between high-bandwidth aerial links and low-bandwidth acoustic underwater channels, all while managing dynamic latency, packet drops, and limited transmission ranges. These interdependencies require simulation environments capable of modelling fully coupled aerodynamics, hydrodynamics, underwater acoustics, and structural motion. However, most existing tools simulate these domains independently, preventing accurate prediction of how multi-platform systems behave in coordinated missions. The absence of such cross-domain coupling severely limits the realism and operational value of mission rehearsals performed in simulation.

1.2.2 Inconsistent Environmental Realism

Environmental modelling in most marine robotics simulators is overly simplified relative to the complexity of offshore conditions. UAV environments frequently represent turbulence and gusts using uniform noise models, overlooking offshore wind spectra, shear gradients near turbines, and turbulence shed by tall structures. USV simulators often approximate wave hull interactions using simplistic sinusoidal motions that omit nonlinear seakeeping behaviours such as slamming, broaching, or parametric roll. AUV simulation environments typically neglect turbidity, thermoclines, suspended sediment, and variable current shear factors that degrade sonar performance, distort acoustic localisation, and reduce navigation accuracy. Without a unified and physics-based environmental engine, simulation tools cannot accurately represent how environmental phenomena interact with platforms and sensors across all domains.

This inconsistency becomes particularly problematic near real infrastructure such as monopiles, platforms, and cable trenches where localised hydrodynamic and aerodynamic disturbances can significantly alter vehicle behaviour. Such limitations contradict the principles of Strategic Engineering, which require highly integrated and realistic representations of the operational environment.

1.2.3 Limitations in Autonomous Behaviour Representation

Although many commercial simulators support basic kinematic modelling, few incorporate realistic autonomy frameworks that mirror field-ready robotic decision-making. Essential autonomy components such as behaviour trees, mission planning algorithms, cooperative task allocation, reactive contingency handling, multi-agent coordination, and human-in-the-loop supervisory control are rarely implemented with the fidelity needed for meaningful validation. This limitation is exacerbated by the frequent replacement of Fossen-style nonlinear control models

with idealised, simplified dynamics that do not reflect actuator saturation, current forces, hydrodynamic coupling, or wave-induced motion.

As a result, simulators fail to evaluate critical autonomy behaviours, including station-keeping near structures, disturbance-aware path planning, energy-constrained mission execution, and reliable collision avoidance under sensor uncertainty. This creates a substantial gap between simulated and real-world autonomy performance, undermining user confidence and slowing the adoption of autonomous inspection systems in industrial practice.

1.2.4 Fragmented Sensor Modelling and Data Fusion

High-quality inspection of marine infrastructure depends heavily on the coordinated use of heterogeneous sensing modalities including optical imagery, sonar systems, RF communications, LiDAR, IMUs, and communication network feeds. Yet most simulation environments treat sensors as ideal or near-ideal devices, failing to incorporate realistic degradation mechanisms such as turbidity, multipath reflections, acoustic noise, scattering effects, communication bandwidth limitations, latency fluctuations, or packet loss.

For example, AUV sonar performance is highly sensitive to seabed texture, suspended sediment levels, thermocline distortions, and vehicle motion dynamics. These factors affect backscatter quality, swath coverage, and localisation accuracy, and therefore must be modelled accurately to evaluate sensor-driven anomaly detection or pipeline tracking algorithms. Without realistic multi-sensor and multi-domain modelling, it becomes impossible to validate defect detection, subsea mesh reconstruction, or coherent UAV USV AUV data fusion strategies. This disconnect conflicts with the Strategic Engineering requirement for real-time, data-driven digital twin integration.

1.2.5 Absence of Digital Twin Integration and Adaptive Simulation

Digital twins are now central to Marine infrastructure management, enabling predictive maintenance and real-time asset health monitoring. However, most simulation environments do not synchronise with digital twin databases, and therefore cannot update asset conditions, degradation states, or predicted failure modes as missions progress. They also lack the ability to ingest live Communication network or environmental data streams, preventing real-time adaptation or scenario evolution based on actual operating conditions. Without such adaptive simulation capability, engineers cannot perform meaningful “what-if”

scenario testing, cross-validate predicted degradation with sensor observations, or evaluate autonomous mission strategies under varying hazard profiles. This limits the effectiveness of simulations as predictive maintenance tools and undermines the broader digitalisation efforts currently underway in the offshore energy and communication sectors

Existing inspection frameworks rarely exploit digital twins capable of synchronizing simulation with field data and adapting to changing conditions, despite evidence from ports and space logistics that such twins enable richer "what-if" exploration and policy testing (Bruzzone et al. 2011; Bruzzone et al. 2021). Experience with HLA-based federations shows that adaptive simulations can be continuously tuned against observed behavior, improving both predictive accuracy and decision support (Bruzzone et al. 2011; Bruzzone et al. 2021). Currently, it is estimated that only about 15% of ports worldwide have adopted adaptive digital twin frameworks, compared to the majority still relying on traditional systems, highlighting a significant gap and opportunity for modernization.

1.2.6 Inadequate Human Machine Interfaces for Multi-Domain Operations

Supervising heterogeneous autonomous systems in offshore environments requires advanced human machine interfaces capable of presenting complex 3D spatial information in an intuitive and comprehensible manner. Yet most existing tools rely on conventional 2D screens and fragmented dashboards that cannot efficiently represent Spatial Decision Interface underwater environments, aerial trajectories, seabed structures, or dynamic digital twin states.

These limitations hinder situational awareness and increase operator workload an issue particularly relevant under IMO MASS regulatory expectations, which emphasise meaningful human oversight and transparency in autonomous decision-making. Operators must be able to understand autonomy intentions, detect anomalies, intervene when needed, and supervise multiple robotic assets simultaneously. Current visualisation systems do not support such requirements, compromising operational safety and reducing trust in autonomy-assisted inspection workflows.

1.2.7 Deficiencies in Hazard and Anomaly Scenario Modelling

Marine infrastructure is exposed to numerous hazards including scour evolution, cable free-span formation, corrosion growth, fatigue cracking, accidental anchor drags, and storm-induced loading. These hazards evolve dynamically and influence structural integrity in ways that are critical for inspection planning. However, most simulation environments treat infrastructure as static meshes, lacking the ability to represent evolving defects, structural responses, or sensor structure interactions such as changes in acoustic reflectivity. Without realistic and dynamic hazard modelling, autonomous mission profiles cannot be stress-tested under representative failure scenarios. Engineers are unable to validate whether robotic systems can detect early-stage anomalies, adapt sensing patterns based on observed degradation, or maintain effective performance under multi-hazard conditions. Consequently, simulation tools fail to serve as reliable platforms for design, evaluation, and training in Marine offshore inspection.

1.2.8 Research Objectives

To address the limitations identified in the previous sections, this thesis pursues a set of integrated research objectives that collectively advance the state of Marine marine infrastructure inspection. Each objective is strategically formulated to bridge existing gaps in modelling, autonomy, data fusion, and human–system interaction.

Multi-Domain Operational Modelling : The first objective is to develop a comprehensive operational model capable of representing the air, surface, subsurface, and seabed domains as an interconnected operational environment. This model incorporates realistic environmental interactions including wind shear, wave loading, current stratification, turbidity variations, and sediment transport as well as dynamic infrastructure behaviour. By capturing the physics and constraints of each operational layer simultaneously, the model supports the high-fidelity simulation required for modern autonomous inspection missions.

System-of-Systems Architecture : A second objective is to design a modular system-of-systems architecture that integrates UAVs, USVs, AUVs, infrastructure models, sensors, and communication links into a coherent operational ecosystem. This architecture supports interoperability across heterogeneous assets and ensures that aerial, surface, and underwater platforms can coordinate tasks, share situational awareness, and operate safely under Marine regulatory requirements.

Hazard-Centric Scenario Framework : The third objective is to construct a Marine-oriented scenario framework that emphasises engineering disturbances rather than adversarial behaviours. The scenarios include scour progression, fatigue-induced cracking, corrosion evolution, cable free-spans, unintentional anchor drags, and storm-induced structural loading. This approach aligns explicitly with marine engineering priorities.

Autonomous Behaviour Modelling : Another objective is to model the autonomous behaviours of UAVs, USVs, and AUVs using principles grounded in marine vehicle control theory, particularly the nonlinear dynamics and guidance formulations established by Fossen (1994). The behaviours include navigation, sensing optimisation, cooperative mission execution, contingency management, and adaptive task allocation. These models allow vehicles to interact with dynamic environments and infrastructure safely and intelligently.

Data Fusion and Digital Twin Integration : A fifth objective is to implement a real-time data pipeline that fuses heterogeneous sensor data including optical imagery, sonar outputs, acoustic telemetry, inertial measurements, and environmental observations into a unified digital twin. This integration supports anomaly detection, structural health monitoring, and predictive maintenance consistent with modern resilience engineering and with Strategic Engineering principles (Bruzzone et al., 2023).

Extended-Reality (XR) Decision-Support Interface : The sixth objective is to develop an Extended-Reality (XR) interface that allows human supervisors to explore multi-domain environments immersively. Through VR and MR environments, operators can inspect digital twin models, visualise seabed and structural features in 3D, and supervise autonomous fleets with improved situational awareness. This aligns with emerging findings in the M&S community (Bruzzone, Longo & Massei, 2023).

Scenario-Based Validation : The final objective is to validate the proposed framework using scenario-based simulations representing realistic operational contexts including post-storm assessment, routine inspection sweeps, and targeted anomaly investigations. Validation focuses on feasibility, accuracy, robustness, energy use, mission duration, and human–autonomy interaction performance.

Contributions of the Thesis : This thesis contributes at four interdependent levels theoretical, methodological, technical, and operational establishing a rigorous marine-focused foundation for autonomous infrastructure inspection.

Theoretical Contribution : At a theoretical level, the thesis extends the discipline of Strategic Engineering into the domain of offshore infrastructure inspection. It formalises how uncertainty, environmental complexity, and cross-domain coupling can be modelled within a closed-loop digital twin architecture. This contribution builds on and advances the foundations laid by Bruzzone and collaborators (Bruzzone et al., 2021), demonstrating how Strategic Engineering can guide resilient, intelligent inspection of multi-domain marine environments.

Methodological Contribution : Methodologically, the thesis proposes the first integrated multi-domain simulation framework that couples aerodynamic, hydrodynamic, underwater acoustic, and structural models with autonomous systems and dynamically evolving hazard models. This framework moves beyond the siloed simulators that dominate current practice and provides a unified environment for mission rehearsal, resilience assessment, and design-space exploration.

Technical Contribution : On the technical front, the thesis introduces an XR-enabled command-and-control interface and a complete digital twin integration pipeline. These tools link autonomous robotic sensing with asset-health models, enabling operators to supervise missions, inspect digital twins in immersive environments, and make informed decisions more effectively. These contributions align directly with ongoing research in simulation-driven marine inspection (Bruzzone et al., 2023).

Operational Contribution : Operationally, the thesis provides a validated Concept of Operations (CONOPS) for a heterogeneous UAV–USV–AUV triad deployed collaboratively for Marine offshore inspection tasks. The results demonstrate that cooperative autonomous inspection significantly improves safety, reduces human exposure to hazardous conditions, and increases mission scalability. The proposed CONOPS is framed explicitly within emerging MASS regulatory discussions (IMO, 2021), ensuring compliance with Marine maritime governance.

In summary, the thesis argues that the long-term resilience of critical marine infrastructure depends increasingly on the intelligent, coordinated, and strategically engineered deployment of autonomous systems, integrated with digital twins and overseen by human supervisors within an explicitly Marine, regulation-aligned framework. These contributions collectively advance the scientific and practical foundations needed for safe, effective, and scalable inspection of offshore assets.

Chapter 2

STATE OF THE ART

2.0.1 Marine Infrastructure Systems

Port-scale digital twins such as ALACRES2 model marine infrastructures as complex systems that couple energy facilities, logistics terminals, and urban interfaces, allowing stakeholders to study how changes in traffic, fuels and technologies affect both efficiency and risk (Bruzzone et al. 2011); (Bruzzone et al. 2021). For example, consider a scenario where a design tweak at a single logistics terminal improves container handling efficiency but inadvertently increases truck traffic bottlenecks at the main entrance of the port. This ripple effect causes delays that affect not only terminal operations but also city traffic and air quality, highlighting the interconnected nature of the port-city interface. Complementary statistical analyses of accidents confirm the importance of viewing ports as system-of-systems, where local design or policy changes can trigger global effects on safety and performance.

Modern marine infrastructure including offshore wind farms, subsea pipelines, submarine power and fibre-optic cables, floating production systems, port terminals, and coastal protection structures constitutes a critical backbone for global energy, digital connectivity, and industrial logistics. Across the engineering literature, these assets are consistently described as multi-hazard systems exposed to mechanical, environmental, and operational stressors that evolve over time. Offshore structural elements are vulnerable to corrosion influenced by oxygen concentration, salinity, temperature gradients, and coating degradation, while wave-induced cyclic loading accelerates fatigue and crack propagation in welded joints and tubular components. Marine growth adds hydrodynamic drag and obscures inspection surfaces, complicating both visual and sonar-based assessments and affecting long-term structural performance. Because of these degradation pathways, researchers increasingly emphasise

2.1 Inspection and Monitoring Methods

predictive and multi-sensor inspection strategies that integrate autonomous systems with computational modelling, rather than relying solely on periodic manual surveys.

For buried or partially buried infrastructure such as pipelines and subsea cables, the literature documents hazards arising from sediment mobility, scour and free-span formation, turbidity-current impacts, and mechanical damage from fishing gear and anchor drags. These phenomena have been widely observed through AUV/ROV surveys and long-term monitoring campaigns. Recent studies highlight the improved fidelity of AUV-based multi-beam bathymetry, side-scan sonar, and magnetic detection methods for identifying exposure, burial loss, or deformation along cable and pipeline corridors. Similarly, coastal and port structures face serviceability issues including concrete spalling, armour unit displacement, liquefaction-driven settlement, and scour at pile foundations. UAV photogrammetry, USV-mounted LiDAR, and AUV-based sonar imaging have become common in modern harbour and coastal engineering workflows, reflecting the shift toward higher-resolution, multi-domain inspection technologies. Taken together, this body of work establishes marine infrastructure as an intrinsically complex system-of-systems, one that demands integrated inspection frameworks capable of fusing aerial, surface, and subsurface data sources precisely the gap addressed by strategic-engineering approaches (Bruzzone et al., 2021); (Gotelli & Bruzzone, 2022).

2.1 Inspection and Monitoring Methods

2.1.1 Traditional Inspection Practices

Conventional inspection practices have historically depended on human divers, crewed vessels, and tethered ROVs. Although divers provide exceptional situational awareness in confined or geometrically complex spaces, the method is constrained by depth limits, safety risks, limited endurance, variable human performance, and dependency on favourable sea states. Diver-based logs often lack repeatability and spatial coverage, making them inadequate for large-scale or time-critical inspections. Tethered ROVs mitigate some diver-related risks but introduce limitations associated with umbilical drag, restricted operational envelopes, and operator fatigue. Comparative trials show that ROVs often struggle to match the efficiency and coverage of free-swimming AUVs, especially over long pipeline or cable routes. Moreover, traditional methods are inherently reactive, activated only after anomalies are suspected or failures have occurred, exacerbating maintenance delays and increasing lifecycle costs.

2.1.2 Evolution of Autonomous Inspection Technologies

The transition toward autonomous and semi-autonomous inspection technologies has been driven by the need for higher-frequency monitoring, reduced operational risk, and greater spatial coverage. Autonomous systems AUVs, USVs, and UAVs now perform dense spatial sampling, repeated surveys, and long-duration monitoring missions with minimal human exposure. Research from the University of Genoa, led by Bruzzone and colleagues, has demonstrated the value of simulation-based planning tools for autonomous inspection missions, where strategic engineering and agent-based models are used to validate inspection plans before deployment (Bruzzone et al., 2021); (Sinelsikov & Bruzzone, 2021). These approaches help shift from reactive to proactive inspection regimes, enabling predictive-maintenance strategies supported by continuous monitoring and digital twins.

Recent digital-twin experiments on autonomous vehicles provide systematic benchmarks of perception architectures such as SSD and YOLO under synthetic and real video feeds, quantifying trade-offs between detection rate, false positives and computational cost (Bruzzone et al., 2023). These results highlight the need to validate sensor configurations and algorithms in realistic simulated environments before deploying autonomous inspection assets in industrial and marine settings.

2.2 Autonomous Systems in Marine Inspection

Autonomous platforms now form the technological foundation of modern marine inspection systems. Their complementary sensing capabilities and operational envelopes enable consistent, scalable surveillance across air, surface, and underwater domains. Cooperative systems are especially important for offshore energy and telecommunications infrastructures, where spatial scales exceed the capabilities of a single platform and where mission success depends on the coordinated behaviour of multi-domain assets (Paull et al., 2018); (Bruzzone et al., 2023).

2.2.1 UAVs

UAVs provide rapid-deployment, high-resolution inspections of topside structures such as turbine blades, nacelles, helidecks, flare booms, and platform decks. Photogrammetry and LiDAR-equipped UAVs generate accurate 3D reconstructions and detect surface degradation with higher precision than many traditional visual methods. Their offshore use, however, is constrained by wind gusts, wake turbulence from turbines, GNSS multipath near metallic structures, and restricted

2.2 Autonomous Systems in Marine Inspection

endurance. These challenges necessitate robust guidance and control architectures, validated through high-fidelity simulations (Fossen, 1994); (Bruzzone et al., 2021). UAV operations increasingly integrate with USVs for at-sea launch, recovery, and battery management, reflecting the shift toward cooperative aerial–surface operations.

2.2.2 USVs

USVs enable persistent surface-layer sensing using multibeam sonar, LiDAR, meteorological sensors, and optical systems. Their long endurance and payload flexibility position them as central nodes within heterogeneous autonomous fleets. Recent strategic-engineering studies recognise USVs as operational nexuses capable of providing GNSS-referenced navigation corrections to AUVs, acting as communication gateways between underwater acoustic channels and satellite/radio networks, and supporting UAV recovery or recharging (Bruzzone et al., 2023); (Gotelli & Bruzzone, 2022). Hybrid USVs powered by solar or wind energy further extend mission durations, aligning with sustainable monitoring paradigms.

2.2.3 AUVs

AUVs remain indispensable for subsea inspection due to their autonomy, depth capability, and use of advanced acoustic/optical sensing. They deliver high-resolution imagery, multibeam bathymetry, cathodic-protection measurements, and video inspections under low-visibility conditions. Navigation remains a limiting factor: inertial drift, low-bandwidth acoustic communication, and energy constraints complicate long-duration missions. Research in terrain-relative navigation, Doppler velocity log (DVL) integration, acoustic positioning, and cooperative navigation with USVs has addressed many of these challenges. EU-funded research programmes (H2020 OCEAN-E, MATS) have further expanded interoperability frameworks for multi-platform subsea autonomy.

2.2.4 Multi-Agent Coordination and Heterogeneous Fleet Operations

Coordinating a heterogeneous fleet across air, surface, and subsea domains presents complex challenges related to task allocation, bandwidth-limited communications, environmental uncertainties, and safety constraints around structures. Strategic-engineering research from Bruzzone, Massei, Gotelli and Sinelschikov has produced modelling and simulation frameworks combining agent-based models, discrete-event simulation, and AI-based coordination tools that evaluate multi-agent cooperation under dynamic environmental

2.3 Digital Twins and Simulation for Marine Infrastructure Management

conditions (Bruzzone et al., 2021); (Bruzzone et al., 2023). These models support decision-making by generating feasible inspection plans, predicting resource conflicts, and identifying mission bottlenecks across domains.

Strategic-Engineering simulators for maritime interdiction model coordinated fleets of patrol vessels, UAVs, and support assets driven by intelligent agents, showing that genetic-algorithm-based planners can significantly improve detection and interception performance under resource constraints (Bruzzone, 2021). A recent study indicated a 25% improvement in detection accuracy and a 30% reduction in response times, underlining the substantial benefits of this approach. The same principles of heterogeneous asset coordination and AI-supported planning are directly applicable to multi-platform inspection of critical marine infrastructures.

2.3 Digital Twins and Simulation for Marine Infrastructure Management

Digital twins have emerged as a transformative tool for managing complex marine assets across their lifecycle. They integrate real-time structural, environmental, and operational data into dynamic computational models that forecast asset response under evolving conditions. A digital twin typically comprises the physical asset, a high-fidelity digital representation, and a bidirectional data interface. In marine settings, digital twins are used for modelling corrosion progression, fatigue accumulation, scour evolution, and structural behaviour under hydrodynamic loading. These capabilities are increasingly supported by IoT-enabled sensor networks deployed across turbines, pipelines, platforms, and coastal structures.

Virtual labs and port-scale digital twins have been used to simulate oil spills, toxic gas dispersion, vessel traffic and energy flows, providing quantitative assessments of environmental impact and risk for alternative procedures and investments. Interoperable HLA-based frameworks validated in both port protection and lunar-base logistics demonstrate that Systems-of-Systems representations can reuse heterogeneous models while maintaining coherent time management and data exchange, a key requirement for complex marine infrastructures (Bruzzone et al., 2021).

Digital-twin applications in offshore wind include vibration-based monitoring, load estimation, and predictive maintenance models. For pipelines and cables, digital twins support burial prediction, free-span risk detection, VIV fatigue analysis, and anomaly correlation with environmental events. For coastal

2.4 Extended Reality (XR) in Engineering, Inspection and Decision Support

structures, they track armour movement, scour formation, and material degradation. Despite progress, large-scale digital-twin deployments remain limited by data-fusion challenges, lack of unified modelling standards, and difficulties in integrating multi-domain sensing limitations directly addressed by strategic engineering and the marine simulation architectures developed within this thesis (Bruzzzone & Massei, 2016); (Gotelli & Bruzzzone, 2022).

2.4 Extended Reality (XR) in Engineering, Inspection and Decision Support

XR technologies including VR, AR, and MR have gained prominence as tools for immersive visualisation, decision-support, and training in marine engineering contexts. XR environments allow engineers to interact directly with complex 3D models, digital twins, and multi-domain simulation outputs. For offshore infrastructure, XR improves situational awareness by visualising spatially complex hydrodynamic fields, structural geometries, seabed topography, and fused multi-sensor datasets from UAVs, USVs and AUVs.

XR systems enhance training by enabling operators to rehearse hazardous procedures such as ROV/AUV deployment, UAV landing on USVs, confined-space inspections, and emergency response operations in safe, controlled simulations. Studies indicate that XR-based training can significantly improve decision-making performance and reduce associated operational costs (Wang et al., 2022); (Bruzzzone et al., 2023). Collaborative XR environments such as CAVE systems enable multidisciplinary teams to interact within the same virtual space, supporting mission planning, risk assessment, multi-hazard scenario evaluation, and digital-twin visualisation. In the context of autonomous inspection, XR supports human-in-the-loop oversight a requirement increasingly aligned with IMO MASS regulatory expectations by providing transparent access to autonomy states, mission plans, and environmental constraints.

XR-based simulators such as COYOTE for ports and mixed-reality training systems for industrial control rooms have shown measurable improvements in operator accuracy, reaction times, and adherence to safety protocols (Bruzzzone et al., 2024); Bruzzzone, Sinelshchikov, Massei, and Gadupuri, 2024). In addition, XR interfaces linked to simulation and real-time data have been used to support maintenance and supervision along production lines and harbor plants, suggesting strong potential for human-centred decision support in marine infrastructure inspection (Bruzzzone et al., 2024).

Chapter 3

METHODOLOGY

3.1 Rationale for the Chosen Methodology

The methodological choices adopted in this thesis stem from the characteristics of the simulator and from the nature of the research questions raised in the introductory chapter. The simulator models marine infrastructure through structural degradation processes, hydrodynamic forcing, seabed interaction and multi-domain vehicular activity. It does not incorporate industrial-control logic such as SCADA or DCS systems, and it does not emulate protection relays or real-time plant automation. Its orientation is instead toward the interaction between environmental disturbances, structural behaviour, communication constraints and the movement and sensing capabilities of inspection platforms.

The modelling challenges relate primarily to the fact that offshore infrastructure behaves as a coupled physical environmental system rather than a set of isolated components. Loads, degradation, marine traffic, inspection operations and communication constraints influence one another over time. Environmental disturbances, including storm-driven waves, currents, sediment mobility or turbidity, may combine with operational or navigational effects, such as the passage of a service vessel or the drift of a fishing vessel over a sensitive area. Where vessels and autonomous systems operate close to foundations or cable routes, small deviations in navigation can have disproportionate consequences for both safety and asset integrity. The literature on structural degradation confirms that none of these influences evolves linearly: corrosion rates vary with immersion cycles and oxygen availability, scour develops as a function of sediment characteristics and flow regime, and free spans can appear and disappear depending on seabed mobility (Melchers 2003; Booij, Ris & Holthuijsen 1999; Nielsen 1992; Bai, Marsden & Li 2021).

3.2 Defining the Core Methodology: Strategic Engineering

Traditional engineering assessments often treat these processes separately, analysing structural fatigue, seabed stability, or vessel motion in isolation. This separation makes it difficult to capture the interactions that can be decisive in offshore environments. A purely static representation is inadequate when infrastructure behaviour depends on the sequence of events and on feedback between operations and environmental conditions. A methodology was therefore required that could integrate multiple domains, incorporate temporal evolution and support the continuous reassessment of risk as new information becomes available.

The simulator inherently supports this approach through its ability to represent environmental forcing, structural processes, inspection platform behaviour and communication constraints within a common spatial and temporal frame. Rather than running analyses as isolated evaluations, the thesis adopts an iterative framework in which simulated actions generate new observations, and these in turn modify subsequent evaluations. This usage aligns with established digital-twin and decision-support concepts in the literature, where models are progressively refined by new data and used to anticipate the consequences of operational choices (Qi & Tao 2019; Jones, Snider & Njuguna 2020; Bruzzone et al. 2021).

This rationale supports a methodology based on Strategic Engineering, which offers a structured way to integrate modelling, simulation, communication processes, operation of autonomous platforms and human supervisory intervention within a single analytical process. The remaining sections of this chapter describe how this methodological framework is implemented to fit the actual capabilities of the simulator and the constraints of offshore operational practice.

3.2 Defining the Core Methodology: Strategic Engineering

Strategic Engineering, as defined in earlier work on simulation-based analysis of complex marine and industrial systems, provides a structured way to combine modelling, simulation, data flows, autonomous systems and operator oversight (Bruzzone et al. 2011; Massei & Bruzzone 2010). The methodology is designed to support decision-making rather than to execute fully automated optimisation. It integrates environmental and structural models with the movement and sensing of UAVs, USVs and AUVs, together with the communication constraints that limit real-time coordination.

3.2 Defining the Core Methodology: Strategic Engineering

The approach adopted in this thesis follows the established view that Strategic Engineering operates through a closed loop. The simulator produces a representation of environmental and infrastructural conditions; autonomous or semi-autonomous inspection trajectories are executed; and the resulting information is interpreted by the operator through the Marine Spatial Decision Interface (MSDI). Each cycle refines the understanding of structural risk and guides the next inspection or intervention.

3.2.1 Data Fusion and Elaboration

The first stage in each analytical cycle is the consolidation of information available in the simulator. Environmental data include wave fields, currents, visibility, turbidity and sediment conditions, each evolving in time and space according to hydrodynamic and seabed-interaction models (Booij, Ris & Holthuijsen 1999; Chen, Liu & Beardsley 2003; Nielsen 1992). Structural data derive from the degradation models implemented in the simulator, such as corrosion progression, fatigue accumulation or scour development.

The simulator also records vehicle trajectories and sensor detections, including sonar, optical and multibeam measurements, all subject to the uncertainties described in the literature for underwater and aerial sensing (Blondel 2010; Hughes Clarke 2018; Jaffe 2015). These sources differ in time resolution, noise characteristics and spatial coverage. The data elaboration stage therefore concentrates on aligning them into a coherent representation of the state of the scenario. The central question at this stage is to establish the present condition of the infrastructure and the surrounding environment.

3.2.2 Modelling and Simulation

Once a consolidated state has been derived, the simulator is used to evaluate the consequences of possible actions or environmental evolutions. Structural behaviour is simulated under varying loads or seabed conditions, while disturbances such as storms or vessel incursions can be represented using the environmental and operational models available in the simulator (Covault et al. 2022; Paull et al. 2018). The mobility of AUVs, USVs and UAVs follows simplified but domain-appropriate kinematics, without invoking high-fidelity hydrodynamic control laws. This ensures consistency with the simulator's capabilities while still enabling meaningful evaluation of inspection coverage, timing and risk.

The simulation phase explores how different inspection or patrolling strategies influence coverage, detection capability and safety margins. Scenarios differ in

3.2 Defining the Core Methodology: Strategic Engineering

terms of environmental forcing, vehicle allocation, route planning or avoidance of sensitive areas. This aligns with approaches found in distributed simulation of maritime systems (Bruzzone et al. 2011) and in multi-agent coordination studies (Cao et al. 2020).

The modeling approach adopted here builds on interoperable simulation frameworks already validated in marine interdiction, port crisis response, pandemics and space logistics, all of which combine agent-based and discrete-event models with realistic infrastructure and environmental representations (Bruzzone et al., 2021). These case studies show that such models can reproduce key phenomena traffic congestion, smuggling behaviors, accident evolution and logistics bottlenecks making them a solid foundation for marine infrastructure inspection scenarios (Bruzzone et al., 2022).

3.2.3 Decision Support

The third stage interprets simulation results and provides guidance to the operator. Instead of presenting raw outputs, the simulator highlights the implications of different inspection patterns, environmental conditions or asset states. The MSDI plays a central role here by presenting the offshore area in a spatially intuitive form and allowing the operator to explore alternative deployments. This approach is consistent with research showing that spatially structured representations improve understanding in complex marine and industrial domains (Sutherland et al. 2019; Carbonell-Ruiz et al. 2021).

The intent is not to automate decision-making but to enhance the clarity of the operator’s reasoning. The simulator offers indications of inspection completeness, potential hazards and likely structural evolution, but the formulation of priorities remains a human responsibility, consistent with current regulatory expectations for autonomous systems (IMO 2021).

3.2.4 Adaptive Refinement

The final stage consists of reintegrating the results of each iteration into the next. Observations from vehicle movement, sensor detections and disturbance effects are compared with earlier expectations, allowing the operator to understand discrepancies and refine subsequent plans. While the simulator does not implement machine-learning techniques for automated model calibration, the methodological loop remains valid: human interpretation governs the improvement of strategies and the identification of new inspection priorities. This structure reflects the

3.3 Human-in-the-Loop Interaction and XR Support

iterative principles of Strategic Engineering described in previous research (Bruzzone et al. 2021).

3.3 Human-in-the-Loop Interaction and XR Support

The simulator is designed for operator-centred analysis. It is not an autonomous-decision system and does not attempt to replace human reasoning. Instead, it integrates vehicle movement, environmental processes and structural behaviour in a way that allows operators to assess scenarios through the Marine Spatial Decision Interface. High-density data from sensors and environmental fields can impose a cognitive burden if presented as raw numerical streams. Previous studies show that immersive or semi-immersive visualisation reduces the difficulty of interpreting spatially distributed information in engineering contexts (Sutherland et al. 2019; Wang et al. 2022). To support this, the simulator provides an XR-enabled view of the offshore area, enabling the inspection of cable routes, foundations, pipelines and vehicle tracks. The XR interface is not used as a control mechanism but as an interpretative tool to help users understand spatial relationships and rehearse different strategies.

This configuration resonates with the human-in-the-loop principles emphasised in recent studies of maritime autonomy, where operator judgement remains decisive even when autonomous or semi-autonomous vehicles are deployed (Clément et al. 2022; IMO 2021). The simulator therefore positions XR as a cognitive support rather than an automation layer, integrating visual reasoning with structural and environmental understanding.

Human-in-the-loop experiments with COYOTE in ports and XR-based training for industrial control rooms demonstrate that embedding users in immersive, data-driven simulations enhances both learning outcomes and safety metrics Bruzzone, Giovannetti, Gadupuri, and Karim, 2024; Bruzzone, Sinelshchikov, Massei, and Gadupuri, 2024. The present methodology generalizes this concept by using XR front-ends as interactive windows into the simulation and digital-twin backends, allowing operators and planners to explore complex multi-domain offshore situations with real-time feedback on risk and performance indicators.

3.4 Validation Testbed: Multi-Domain Offshore Scenario

3.4.1 Scenario Description

The scenario used throughout this thesis is designed to represent a simplified yet credible offshore area containing multiple types of infrastructure. It includes foundations, cable routes and pipelines, together with harbour structures and navigational channels. The scenario uses real bathymetric surfaces, varying sediment types and representative hydrodynamic fields based on established coastal-ocean models (Booij, Ris & Holthuijsen 1999; Chen, Liu & Beardsley 2003).

Disturbances such as storms, turbidity events and vessel incursions are simulated using the environmental and operational subsystems available. Fishing vessels and service vessels follow traffic patterns that may inadvertently intersect areas where inspection vehicles operate. Deliberate intruder-type vessels can also appear, though their behaviour is modelled only as anomalous movement patterns rather than hostile action.

3.4.2 Disturbance and Hazard Processes

The simulator incorporates structural and seabed disturbances including corrosion progression, fatigue processes, scour, sediment mobility and free-span formation. These processes reflect established models in the literature (Melchers & Jeffrey 2018; Fuhrman et al. 2020; Bai, Marsden & Li 2021). They evolve dynamically, creating a need for repeated inspection and for adaptive planning of trajectories.

Communication disturbances are also represented. Environmental conditions such as wave height, distance and occlusions influence radio links between UAVs, USVs, AUVs and the shore station. Acoustic communication for underwater assets is subject to range limitations and noise, consistent with established underwater-acoustics theory (Lurton 2010). Satellite communication is included conceptually to model long-range connectivity.

The figure will show the schematic arrangement of radio, acoustic and satellite communication links between UAV, USV, AUV and shore.

3.4.3 Role of the Testbed

The testbed provides a controlled environment to evaluate inspection strategies under different disturbance conditions. It allows repeated execution of scenarios

3.5 Marine Spatial Decision Interface (MSDI)

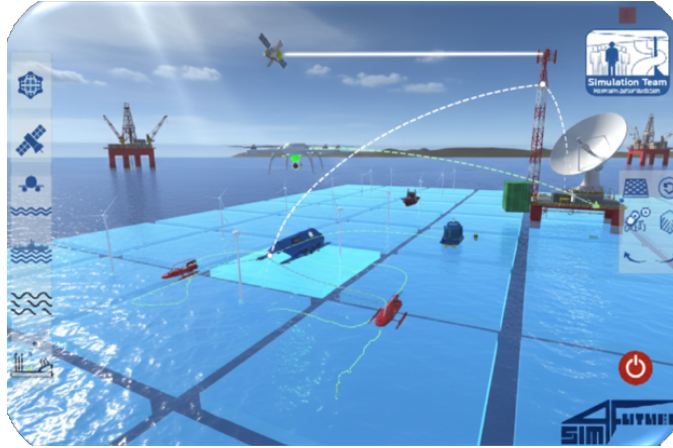


Figure 3.1: MSDI communication architecture.

to understand how structural risks evolve and how vehicle deployment influences coverage. It also provides a consistent basis for evaluating how operators interact with the MSDI and how XR visualisation influences decision-making.

3.5 Marine Spatial Decision Interface (MSDI)

The Marine Spatial Decision Interface serves as the primary operational and analytical interface for the thesis. It organises the offshore area into a three-dimensional spatial grid that represents airspace, surface, water column and seabed. In contrast to the earlier “Spatial Decision Interface command interface” terminology, which could imply fluid-dynamics modelling, the MSDI is explicitly a spatial decision tool. It supports operator reasoning by enabling the inspection of areas, the prioritisation of zones and the evaluation of potential routes.

The interface allows users to move focus between the regional scale and specific infrastructure components, observing the effects of disturbances or planned deployments. It also aggregates information so that individual vehicle kinematics do not overwhelm the user. Vehicles are presented as mission entities rather than as continuously controlled dynamic systems.

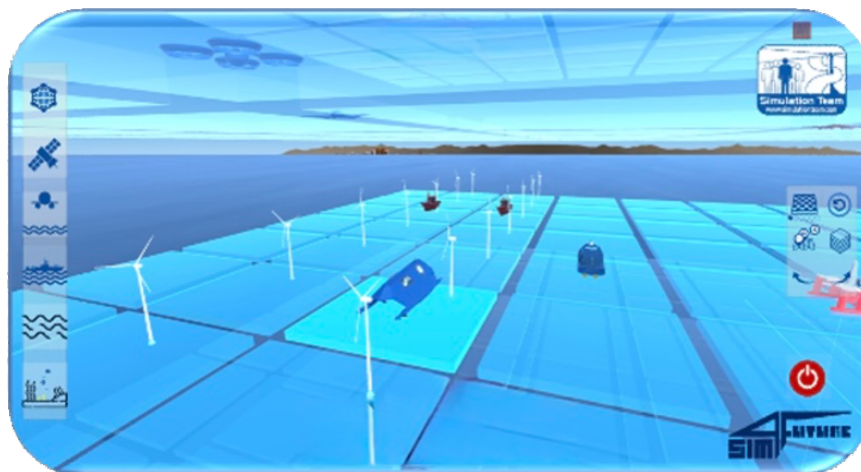


Figure 3.2: Marine Spatial Decision Interface (MSDI) showing layered air–surface–subsea domains and infrastructure elements.

3.6 Intelligent Agents and Interoperability

3.6.1 Intelligent Agents for Inspection Coordination

Within the simulator, intelligent agents serve as organisational components that translate user-defined objectives into coherent sets of vehicle tasks. They do not execute high-fidelity motion planning but act as coordination mechanisms that allocate areas, define simple trajectories and adjust behaviour in response to environmental changes. This reflects the conceptual frameworks used in multi-agent marine robotics, while staying within the simulator’s simplified movement models (Dimarogonas et al. 2012; Cao et al. 2020; Visingardi et al. 2023).

The agents also interpret disturbances generated by environmental models. For example, if seabed mobility increases turbidity along a pipeline, the agents can shift inspection focus to areas where visibility remains adequate. This interaction between environmental conditions and the allocation of inspection attention is one of the core analytic benefits of the simulator.

3.6.2 Interoperability through HLA/RTI

The simulator incorporates a working implementation of the High Level Architecture (HLA) through a Runtime Infrastructure (RTI), enabling federation with external models consistent with established standards for distributed simulation (Bruzzone et al. 2011). This capability permits the exchange of

3.6 Intelligent Agents and Interoperability

environmental, operational or asset-state data with other simulators such as weather models, vessel-traffic simulators or additional inspection-vehicle systems when available.

Interoperability design follows patterns already applied in port protection and Moon-base space logistics, where HLA-based federations and dedicated gateways enabled heterogeneous simulators and visual engines to share state and time progression without intrusive changes to existing (Bruzzone et al., 2021). This experience confirms the feasibility of integrating autonomous-system simulators, port digital twins, and serious-game components within a single, coherent inspection and protection environment (Bruzzone et al., 2023).

The integration is practical rather than conceptual: objects and interactions can be published and subscribed across federates. This ensures that the simulator can be extended in future work to incorporate more refined hydrodynamic or communication models without rewriting its core architecture.

Chapter 4

SYSTEM IMPLEMENTATION, PLATFORM AND ENVIRONMENT

Autonomous inspection and protection of marine infrastructure rely on a coordinated fleet of unmanned aerial, surface, and underwater platforms coupled with advanced simulation, data fusion, and decision-support capabilities. The quality, reliability, and safety of inspection outcomes depend directly on the fidelity of each platform’s mechanical design, power system, autonomy stack, navigation subsystem, communication links, and sensor payloads, as well as on how these components are integrated into a coherent multi-domain architecture. This chapter therefore presents the detailed implementation of the multi-domain system introduced conceptually, focusing on three interconnected layers:

Platform and sensor modelling for unmanned aerial vehicles (UAVs), unmanned surface vehicles (USVs), and autonomous underwater vehicles (AUVs); Representation of the extended maritime environment, including cyber-physical infrastructure and communication networks; and Interoperability, intelligent-agent coordination, and digital-twin integration.

The methodology follows a strictly Marine perspective centred on marine infrastructure inspection, environmental monitoring, and resilience analysis. It is explicitly designed to comply with institutional requirements that prohibit war-gaming, combat modelling, or operational defence scenarios. Instead, the framework is used to explore how autonomous systems can support safer, more efficient and more sustainable management of offshore wind farms, subsea power and telecommunication cables, pipelines, harbor structures, and coastal defences, including their protection against accidents, natural hazards, and non-intentional

4.1 System Architecture and Extended Maritime Framework

disruptions.

The chapter is grounded in established research on marine robotics and control (Antonelli 2013; Kinsey et al. 2006), underwater and surface sensing (Blondel 2010; Lurton 2010; Hughes Clarke 2018; Jaffe 2015), and structural health monitoring of marine assets (Melchers & Jeffrey 2018; Lotsberg 2019).

At the system-of-systems level, it draws heavily on the Strategic Engineering and simulation-based engineering work of the Simulation Team at the University of Genoa and its spin-off Sim4Future, who have demonstrated how interoperable modelling and simulation can support complex Marine decision-making in logistics, ports, and industrial systems (Massei & Bruzzone 2010; Bruzzone et al. 2011; Sinelshchikov et al. 2019; Gotelli et al. 2019). Their principles of modular architectures, interoperable simulators, and intelligent agents are adapted here to the context of marine infrastructure inspection.

4.1 System Architecture and Extended Maritime Framework

The autonomous inspection ecosystem is organised around three classes of unmanned platforms operating in a shared Extended Maritime Framework (EMF). The EMF is a conceptual representation that encompasses the air column, sea surface, water column, seabed, coastal interface, and associated cyber-physical information systems. It thus recognises that modern marine infrastructure is simultaneously physical and digital: an offshore wind turbine or subsea cable is embedded not only in water, air, and sediment, but also in supervisory control and data acquisition (SCADA) systems, communication networks, and enterprise asset-management platforms.

Within this framework: UAVs operate in the atmospheric layer, providing high-resolution optical, LiDAR and thermal imagery of towers, nacelles, blades, topside structures, coastal assets and, under suitable conditions, shallow bathymetry and shoreline morphology (Ghani et al. 2019; La Mantia et al. 2022). USVs operate on the sea surface, acting as stable platforms for multibeam bathymetry and side-scan sonar surveys, environmental monitoring, and communication or navigation support for AUVs. AUVs operate in the water column and near the seabed, performing detailed inspection of foundations, pipelines, cables, and seabed morphology using sonar, magnetometers, optical cameras and in-situ sensors (Bingham et al. 2020; Paull et al. 2018).

4.1 System Architecture and Extended Maritime Framework

The EMF introduces an explicit representation of domain interconnectivity. For example, loss of GNSS integrity in the space–air interface affects UAV and USV navigation; damage to a subsea power or data cable in the underwater domain impacts SCADA networks in cyberspace; coastal erosion and storm surge at the land–sea boundary modify seabed scour around foundations and cable burial conditions. The simulation architecture thus maintains a system-wide graph of dependencies so that a change in one domain can propagate through others. This approach reflects the system-of-systems philosophy of Strategic Engineering, where the objective is to support decision-makers by exposing cascading effects and emergent behaviour across large Marine infrastructures (Bruzzone et al. 2011; Bruzzone et al. 2021).

4.1.1 Interoperability via Simulation Gateways

To enable flexible integration of different models and tools, the framework uses an interoperability layer inspired by the ST HLA gateway developed by the Simulation Team at the University of Genoa (Bruzzone et al., 2011; Sinelshchikov et al., 2019). This gateway:

Translates high-level commands from the VCI and the IAs into the specific messages required by physics-based simulators (e.g. Unity Engine, Gazebo, UUV Simulator, acoustic models); Synchronises time across multiple simulators, supporting distributed and federated execution; Allows external simulators or hardware-in-the-loop components to be integrated into the overall architecture.

The system employs a simulation gateway similar to the one tested in the SEE lunar-base federation, which connects Unity-based visualizers and other external clients to the RTI through a WebSocket and JSON interface (Bruzzone et al., 2021). This design allows heterogeneous components autonomous-platform simulators, digital-twin services, analytics modules and XR front-ends to participate in the same federation while preserving their internal implementations. The system is organized into a Simulation/Interoperability Layer and a Control/Observation Layer. The architecture is organised around two tightly connected functional layers: a simulation and interoperability layer that ensures execution and synchronisation of the distributed models, and a control and observation layer that provides operators and analysts with access to the evolving simulation state. Within the simulation and interoperability layer, the Run-Time Infrastructure (RTI) operates as the central mechanism for communication and coordination. In accordance with the principles of the High Level Architecture, the RTI manages time regulation, data exchange and object ownership among the participating federates, enabling the system to function as a coherent federation rather than as

4.1 System Architecture and Extended Maritime Framework

modify mission priorities or adjust environmental and operational parameters injected into the simulation. These controllers do not interact directly with the engine but instead influence it through the same gateway-mediated exchange used by the autonomous agents, maintaining a consistent data pathway. A complementary component, the simulation-engine observer, continuously acquires data produced by the engine, processes it into a form suitable for real-time viewing, and disseminates it to different visualisation devices. This ensures that the simulation state can be inspected through conventional workstation displays, mobile interfaces, or immersive XR viewers without imposing additional computational load on the core engine. The distribution of observation functions across heterogeneous devices is consistent with the extended-reality frameworks adopted in recent Simulation Team studies, which emphasise the value of visual and spatial comprehension when analysing maritime scenarios (Bruzzone, Longo & Massei 2023).

Together, these layers constitute an HLA-inspired distributed simulation environment in which each core domain UAV, USV, AUV, environmental processes, infrastructure condition, digital-twin logic and XR-based visualisation is represented as a federate connected through the RTI. The federates collectively reconstruct the state of a complex offshore scenario by exchanging updates at runtime under RTI coordination. Marine-vehicle federates publish their dynamic states; environmental federates update wave, current and turbidity conditions; infrastructure federates maintain the evolution of structural parameters; and the XR federate retrieves the consolidated state from the observer and renders it for user interaction. This approach mirrors the multi-domain architectures previously validated for ports, supply chains and industrial resilience studies (Bruzzone et al. 2021; Gotelliet al. 2019), but it is adapted here to account for the interplay between autonomous vehicles, marine environmental disturbance and offshore infrastructure inspection.

The result is an architecture in which simulation execution, interoperability and human interaction are treated as distinct but interdependent functions. The RTI ensures consistent and time-regulated information exchange; the gateway translates and routes this information; the simulation engine computes the physical and operational processes; and the observation interfaces allow analysts and operators to examine the evolving scenario in real time. This integrated design provides the foundation for future expansion, including the possibility of federating additional models such as coastal surveillance, meteorological prediction or communication-network simulation, in line with the interoperability objectives outlined in the distributed-simulation literature of Bruzzone, Massei and their collaborators.

4.2 Platform and Sensor Modelling

4.2.1 UAVs

The UAV model represents multicopter platforms (quadrotor or hexarotor) equipped with stabilised sensor payloads. The airframe and propulsion system include brushless DC motors, ESC dynamics, propeller aerodynamics via blade-element theory, and rigid-body inertial characteristics (Mahony et al. 2012; Clément et al. 2022). Thrust and torque are modelled as quadratic functions of rotor speed, allowing the simulation of energy consumption and control response under varying winds and payloads.

Navigation uses a tightly coupled fusion of GNSS, RTK-GNSS when available, IMU data, barometric altitude, magnetometer heading and, when operating close to infrastructure, visual-inertial odometry (Mourikis & Roumeliotis 2007). The Extended Kalman Filter integrates these measurements to estimate six-degree-of-freedom pose and velocity. Environmental disturbances such as wind shear and gusts are represented using spectral wind models, leading to realistic drift and control-effort requirements consistent with offshore UAV experiments (Eriksson et al. 2019; Clément et al. 2022).

The UAV payload suite typically includes an RGB or HDR camera for photogrammetry and corrosion mapping, a LiDAR scanner for dense 3D reconstruction of towers and topside structures, and an infrared camera for thermal anomaly detection along electrical equipment and fluid systems (Tao et al. 2020; Usamentiaga et al. 2014). Optical imagery is degraded according to atmospheric attenuation and scattering (Wang & Wu 2020), while motion blur and camera noise are modelled as functions of platform speed, exposure time, and sensor characteristics (La Mantia et al. 2022). LiDAR measurements include range-dependent noise and reflectance variations, enabling assessment of geometry reconstruction quality. The UAV energy model links rotor thrust, aerodynamic drag, and battery discharge curves, so that endurance limits can be explored as a function of wind conditions, trajectories, and payload combinations (Clément et al. 2022; Keipour et al. 2021).

4.2.2 USVs

The USV model implements a small to medium-size survey vessel, mono-hull or catamaran, with electric or hybrid propulsion and either rudder-based or differential-thrust steering (Manley 2008; Caccia et al. 2018). Hydrodynamics are represented using nonlinear surge–sway–yaw equations, including added mass,

wave-induced forces, quadratic drag, and strip-theory-based wave resistance. This allows the simulation of turning circles, station-keeping performance, and energy consumption under realistic seas.

Autonomy functions cover line-of-sight waypoint tracking, adaptive station keeping, and reactive collision avoidance in the presence of other vessels or floating obstacles. Controllers range from PID and adaptive PID to model-predictive control, depending on scenario complexity (Caccia et al. 2018). The USV carries a multibeam echosounder (MBES), side-scan sonar, possibly a surface LiDAR, and environmental sensors such as CTD and meteorological instruments. Acoustic propagation and beam geometry follow standard sonar physics, including transmission loss, beam footprint, grazing-angle-dependent backscatter, and noise models (Lurton 2010; Hughes Clarke 2018). This enables realistic prediction of bathymetric uncertainty, scour detectability, and pipeline or cable imaging quality.

4.2.3 AUVs

The AUV model describes a streamlined, buoyancy-controlled vehicle capable of low-altitude seabed following and close-range structural inspection. The six-degree-of-freedom dynamics include rigid-body inertia, added mass, lift and drag of control surfaces, nonlinear damping, buoyancy–weight offset, and thruster forces (Antonelli 2013). Configuration parameters are chosen to reflect typical Marine inspection AUVs used for pipeline and cable surveys (Paull et al. 2018; Bingham et al. 2020).

Navigation combines IMU and DVL dead reckoning with occasional USBL position fixes from the USV, terrain-relative navigation using bathymetric maps, and sonar-based SLAM. Error growth and correction cycles are modelled according to published analyses of underwater navigation systems (Kinsey et al. 2006; Paull et al. 2018). The sensing suite includes high-resolution side-scan sonar for long-range seabed imaging, multibeam or interferometric sonar for detailed bathymetry, forward-looking imaging sonar for obstacle avoidance and structural inspection, optical cameras for close-range visual assessment, and magnetometers for detecting buried metallic infrastructure (Blondel 2010; Bruschi et al. 2019; Ridao et al. 2018). Underwater optical imaging is modelled using the Jaffe–McGlamery formulation, which accounts for absorption, scattering, backscatter, and colour shift (Jaffe 2015; Chiang & Chen 2017). Acoustic transmission loss, noise, and seabed scattering follow classical ocean acoustics, allowing simulation of detectability as functions of range, frequency, and seabed type (Urlick 1983; Lurton 2010).

4.2.4 Sensor Physics and Environmental Interactions

The modeling of sensor physics is informed by digital-twin experiments on autonomous vehicles operating in dusty and noisy industrial environments, where LIDAR, cameras and ultrasonic sensors were tested under different boundary conditions. Those results guide the choice of detection ranges, occlusion logic and false-positive behavior in the marine context, ensuring that simulated inspection capabilities reflect realistic strengths and limitations of each modality (Bruzzone et al., 2023).

Across all platforms, sensor performance is tightly coupled to environmental fields. Optical and LiDAR systems are affected by atmospheric visibility, spray, sun glint, turbidity and water depth; sonar performance depends on sound-speed profiles, stratification, seabed roughness, and noise; inertial sensors suffer from drift and vibration; ADCPs measure depth-varying currents but with noise related to seastate and scatterer concentration (Rudnick et al. 2018). These dependencies are represented explicitly so that inspection quality metrics coverage, resolution, signal-to-noise ratio can be predicted as functions of both vehicle behaviour and environmental conditions.

The resulting platform-and-sensor models form the core of the “physics layer” within the simulation framework. When integrated with the environmental and hazard engines, they enable realistic evaluation of inspection strategies, energy budgets, and digital-twin update quality under a wide spectrum of Marine operating conditions.

4.3 Multi-Domain Hazard and Disruption Modelling

To support infrastructure resilience analysis, the system must model not only the nominal operation of platforms and assets, but also a wide variety of **Marine hazards and disruptions** that can affect inspection campaigns and infrastructure performance. Building on the Extended Maritime Framework, the simulation environment therefore represents a set of interlinked hazard processes across the sea surface, underwater world, air, coastal areas, near-Earth space, and cyberspace. The objective is not to imitate armed conflict or offensive operations but to explore how accidents, natural events, equipment faults, and non-intentional human actions can propagate through complex infrastructure systems.

4.3 Multi-Domain Hazard and Disruption Modelling

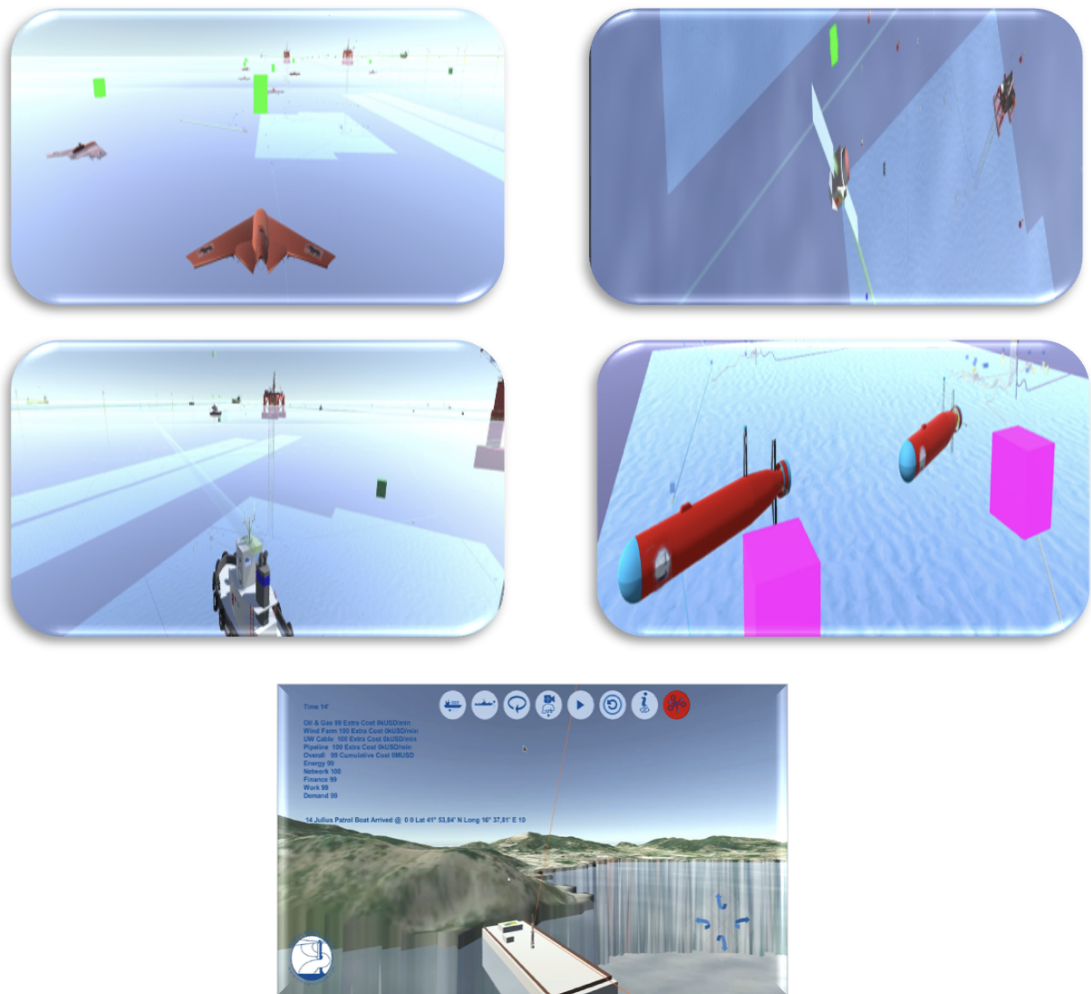


Figure 4.2: Sea Surface, Underwater, Air, Coastal Areas, Space, and Cyberspace.

4.3 Multi-Domain Hazard and Disruption Modelling

A central concept is **domain interconnectivity and system correlation**. Every infrastructure component, communication link, and autonomous platform is modelled as a node in an interdependent system graph, consistent with Strategic Engineering principles (Bruzzone et al. 2011; Bruzzone et al. 2021). When a disturbance occurs such as a cable fault, navigation sensor degradation, or communication slowdown it immediately triggers changes in dependent nodes. For example, damage to a subsea fibre-optic or power cable in the underwater domain yields a measurable loss of bandwidth quality in cyberspace, which in turn affects the information available to operators and autonomous agents. Similarly, a GNSS outage in the space domain leads to increased navigation uncertainty for UAVs and USVs in the air and surface domains, which may cause inspection gaps or higher collision risk if not mitigated by alternative localisation strategies. Within this interdependent framework, several families of Marine disruption scenarios are modelled:

Acoustic modem performance degradation: Environmental conditions such as increased turbidity, strong stratification, or anthropogenic noise can reduce the effective bandwidth or increase latency of underwater acoustic communication links. When AUVs detect anomalies near infrastructure, delayed transmission of these data to the USV or shore-based control centre may temporarily reduce situational awareness. The simulation tracks how alternative communication architectures and relay strategies (e.g. USV repositioning) mitigate such effects.

ICT integrity and data quality issues: Industrial networks, and cloud-based asset-management platforms can suffer from software bugs, configuration errors, hardware failures or congestion. These disturbances may manifest as missing values, delayed updates, inconsistent status flags, or incorrect alarms. The modelling therefore injects data-quality events into the cyber layer and analyses how autonomous inspection planning reacts for example by increasing on-site verification, adjusting inspection priorities, or shifting more reliance onto local sensing and less on remote data.

GNSS signal distortion and loss: GNSS degradation can arise from ionospheric activity, multipath reflection around tall structures, antenna faults, or regulatory restrictions. The system simulates navigation errors for UAVs and USVs under partial or full GNSS loss, requiring them to rely on inertial dead reckoning, visual odometry, or cooperative positioning supported by other vehicles. This is crucial for ensuring that inspection operations remain safe and effective under navigation-challenged conditions.

Multi-platform congestion and operational conflicts: In densely

4.4 Interoperability, Intelligent Agents and XR-Based Decision Support

utilised areas such as large wind farms or busy harbour approaches, several autonomous and crewed vessels, UAVs, and maintenance activities may coexist. The simulation introduces traffic patterns and operational schedules to evaluate how the autonomous fleet avoids conflicts, shares limited air and sea space, and maintains safe distances from third-party traffic in full compliance with Marine navigation rules.

Seabed disturbance and cable exposure: Sediment transport and extreme events can expose previously buried cables or pipelines, creating potential vulnerability to anchors, fishing gear, or further erosion (Carter et al. 2009; Bruschi et al. 2019). The environmental and hazard engines model burial and exposure cycles, scour evolution, and free-span formation (Sumer & Fredsøe 2002; Bai et al. 2021). The autonomous system’s ability to detect such changes early, via MBES, SSS and AUV inspection, is assessed.

Logistics and support disruptions: Offshore assets depend on regular delivery of parts, consumables, and personnel. Weather windows, harbour congestion or supply chain interruptions can reduce the availability of crewed support vessels or specialist technicians. The simulation reflects such constraints in the scheduling layer, illustrating how autonomous inspection can mitigate some of the impact by offering more flexible and lower-risk monitoring options. These scenarios extend the notion of infrastructure protection beyond physical hardware and cyber systems to include the human and logistic subsystems that sustain long-term operation.

By simulating this web of correlated hazards and disruptions in a purely Marine setting, the framework allows engineers and operators to design inspection and maintenance strategies that remain robust under a wide range of realistic “what-if” conditions. Instead of focusing on adversarial behaviour, the emphasis is on resilience, redundancy, and adaptive planning for critical marine infrastructure.

4.4 Interoperability, Intelligent Agents and XR-Based Decision Support

The complexity of the EMF and the richness of sensor data streams mean that human operators cannot be expected to manage low-level control of multiple vehicles while simultaneously interpreting multi-domain information. Following the Strategic Engineering perspective, this thesis adopts an **intelligent-agent (IA) paradigm** in which autonomous software agents manage tactical decisions

4.4 Interoperability, Intelligent Agents and XR-Based Decision Support

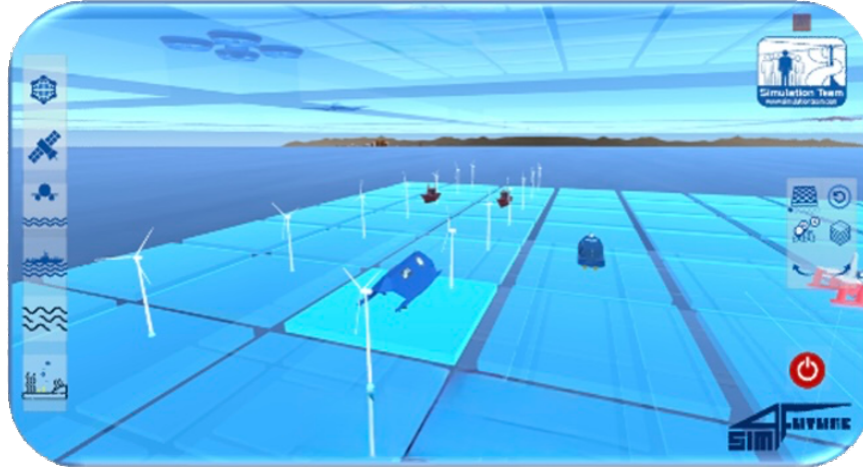


Figure 4.3: Marine Spatial Decision Interface (MSDI)

and coordination, while human experts retain responsibility for strategic objectives, ethical judgement, and high-level supervision (Bruzzone et al. 2011; Sinelshchikov et al. 2019).

Within the distributed simulation architecture, each vehicle, environmental subsystem, and infrastructure asset can have an associated IA responsible for route optimisation, collision avoidance, sensor-task scheduling, communication management, and local fault handling. Higher-level coordination agents allocate inspection tasks among UAVs, USVs and AUVs, taking into account energy budgets, current and forecast environmental conditions, digital-twin priorities, and logistic constraints. These agents implement auction-based or consensus-based task-allocation algorithms commonly used in multi-robot systems, but adapted here for inspection, monitoring and maintenance scenarios rather than security or defence (Kalra et al. 2006; Zhang et al. 2019; Gracias et al. 2021).

Human operators interact with the system through an XR-based command and control interface, conceptually inspired by the “3D chessboard” idea originally developed in other Strategic Engineering projects (Bruzzone et al. 2021). In the current thesis, the interface is repurposed and redesigned as a Marine Spatial Decision Interface (MSDI) that depicts the EMF as a set of vertically stacked layers: seabed and infrastructure, water column with AUV tracks, surface with USVs and third-party vessels, airspace with UAVs, and a cyber-layer representing communication links and data flows. This feature is vital for strategic decision-makers, as it prevents the spatial overcrowding or confusion that often occurs when visualizing heterogeneous assets on a single plane. Each

4.4 Interoperability, Intelligent Agents and XR-Based Decision Support

layer is discretised into cells or sectors that provide a degree of abstraction while retaining geographic accuracy, following the Simulation Team’s experience with grid-based decision-support tools for ports and logistics (Massei, Sinelshchikov & Bruzzone 2010; Gotelli et al. 2019).

Within this XR environment, operators can visualise current and historical inspection coverage, vehicle positions, and hazard indicators; inspect digital-twin states for individual assets, including corrosion level, scour depth, or fatigue utilisation; drag and drop high-level inspection tasks or monitoring objectives onto spatial regions, allowing IAs to derive concrete waypoints and sensing actions; explore “what-if” scenarios interactively, by modifying environmental or infrastructure parameters and observing the simulated IA response.

The XR layer is tightly coupled with the digital twin. As new sensor data arrive from UAVs, USVs, and AUVs, the digital twin updates asset states using data-assimilation and degradation models (Tao & Qi 2019; Jones et al. 2020; Fan & Luo 2021). These updated states, in turn, inform the intelligent agents’ planning decisions and maintain an up-to-date picture of risk and residual life. This closed loop between simulation, real or simulated sensor data, IA planning, and human oversight exemplifies the Strategic Engineering approach promoted by the Simulation Team and Sim4Future: decision-support systems that are not static analysis tools but living, adaptive processes capable of continuous learning and improvement (Bruzzone et al. 2011; Bruzzone et al. 2023).

The summary has presented the implementation of a Marine, multi-domain system for autonomous inspection and protection of marine infrastructure. Starting from the Extended Maritime Framework, it described how UAVs, USVs, and AUVs are modelled in terms of dynamics, navigation, sensing and energy, and how their sensing performance is shaped by environmental physics. It then introduced a hazard and disruption modelling layer that captures the interdependence of physical and cyber domains, not in terms of conflict but in terms of resilience to accidents, environmental extremes, data-quality issues, and logistic constraints. Finally, it outlined how interoperable distributed simulation, intelligent agents, digital twins and XR interfaces drawing extensively on the Strategic Engineering experience of the Simulation Team at the University of Genoa and its Sim4Future spin-off are integrated to provide human-centred decision support for long-term infrastructure monitoring.

The resulting framework forms the basis for the scenario experiments and performance analyses presented in the following chapters, where its ability to support safe, efficient, and robust Marine inspection operations under complex multi-domain conditions is evaluated in detail.

Chapter 5

OFFSHORE PLATFORMS & FIELDS

Offshore platforms, Floating Production Storage and Offloading (FPSO) units, and interconnected underwater production fields represent among the most complex engineered systems currently operating in Marine maritime industries. Ensuring their safe, continuous, and environmentally responsible operation requires a rigorous systems-engineering perspective capable of modelling structural behaviour, operational workflows, digital interactions, and multi-domain sensing and maintenance. As demonstrated in research on underwater robotics (Antonelli 2014), subsea sensing and mapping (Jaffe 2015; Blondel 2010; Hughes Clarke 2018), and digital simulation for critical infrastructures (Bruzzone, Longo and Massei 2014; Gotelli, Bruzzone and Massei 2019), modern marine environments cannot be understood as isolated assets; rather, they behave as interacting systems embedded simultaneously in physical, cyber, and environmental domains.

This chapter therefore extends the simulation framework introduced earlier by providing high-fidelity representations of all key entities composing an offshore production field. Each platform, subsea structure, communication layer, and support system is modelled not as a static object but as a dynamic subsystem whose behaviour varies over time, reacts to environmental conditions, and interacts with other components. In line with strategic engineering principles applied to Marine infrastructure resilience (Bruzzone et al. 2020), the objective is not simply to analyse individual components but to understand the emergent behaviours and vulnerabilities that arise from the coupling of multiple processes, sensors, agents, and operational workflows.

The modelling approach used here supports exclusively peaceful and Marine objectives: safety assurance, predictive maintenance, resilience assessment, continuity of operations, and protection of high-value industrial infrastructure

5.1 Modelling of Critical Offshore Infrastructure and Operational Entities

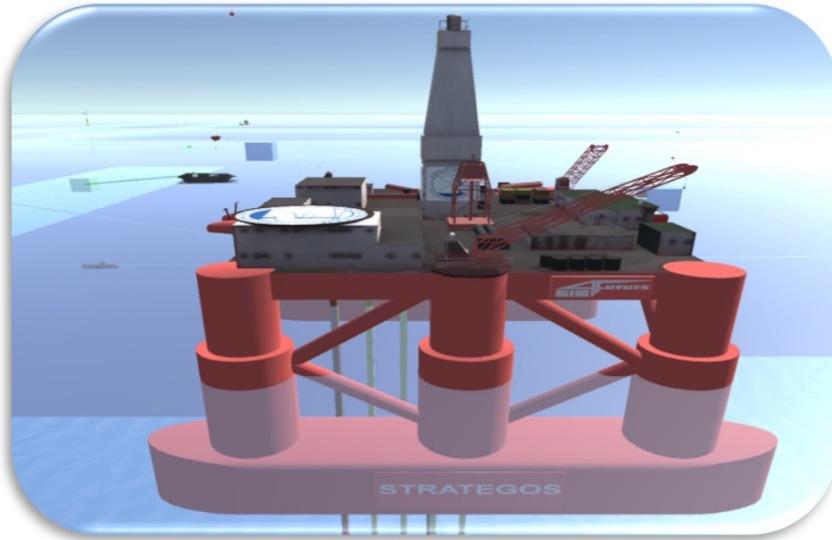


Figure 5.1: 3D Representation of Oil Rig)

from failures, environmental hazards, and system-wide disruptions. This framing is fully aligned with university policies requiring non-military, non-adversarial, and socially beneficial research.

5.1 Modelling of Critical Offshore Infrastructure and Operational Entities

A foundational requirement for any resilience-oriented simulation is the ability to replicate the real-world functional characteristics of offshore energy systems. Offshore platforms and FPSOs are inherently multifaceted installations, comprising mechanical structures, digital control networks, human-machine interfaces, logistical assets, and distributed subsea fields. These are all connected through pipelines, risers, manifolds, umbilicals, and telemetry links that must be represented faithfully to capture systemic vulnerabilities and operational dependencies.

5.1.1 Structural and Mechanical Representation

In order to accurately represent offshore platforms and FPSO systems within a simulation environment focused on Marine resilience and operational continuity, it is essential to model their structural and mechanical characteristics with a level of detail that reflects real engineering practice. These assets are not monolithic

5.1 Modelling of Critical Offshore Infrastructure and Operational Entities

objects; rather, they are multilayered, interdependent assemblies consisting of topside modules, hulls or buoyancy structures, subsea production systems, and an extensive network of risers, pipelines, umbilicals, and control pods. Each component exhibits distinct behaviours influenced by local environmental conditions and operational requirements, and these behaviours must be modelled in a way that captures their dynamic evolution over time. As observed in offshore structural reliability research (Gao and Moan 2020), the complex loading regimes generated by waves, currents, wind fields, and platform motions produce variable stress cycles that accumulate into fatigue damage, making high-resolution modelling indispensable for any study of long-term infrastructure resilience.

Topside modules such as hydrocarbon processing plants, electrical generation units, and safety systems are represented as interconnected functional blocks exhibiting mass, stiffness, and operational constraints aligned with engineering specifications commonly used in FPSO and platform design. These modules are treated not simply as static masses but as active subsystems whose operational states influence, and are influenced by, the broader system context.

For example, the power-generation subsystem imposes vibration loads that alter structural responses in neighbouring modules, while gas treatment units may exhibit thermal expansion effects that change the mechanical interface with their supporting structures. Capturing these relationships enables the model to reflect realistic operational variability and failure propagation patterns.

The hull and buoyancy structures form the core of the platform's global stability envelope and require careful representation of hydrodynamic behaviour, including added mass terms, damping effects, and nonlinear wave-body interactions. In the case of FPSOs, the influence of mooring systems, turret rotation, and wave-induced motions must be included to simulate realistic station-keeping performance. Research by Hughes Clarke (2018) and others in ocean engineering reinforces the importance of hydrodynamic fidelity, as seemingly small deviations in modelling can significantly alter predictions of heave, surge, and pitch, which in turn affect riser tensions, fatigue accumulation, and allowable operational windows for inspection activities. Risers and flexible pipelines constitute another critical structural element of offshore production systems. These conduits experience constant mechanical loading due to hydrodynamic drag, platform motion, internal pressure fluctuations, and seabed interaction. Their behaviour cannot be isolated from the broader structural context; instead, the simulation must incorporate coupled dynamics that allow platform motion to influence riser bending stresses and allow environmental conditions to modulate pipeline free-span vibrations and seabed scour. This interdependence

5.1 Modelling of Critical Offshore Infrastructure and Operational Entities

is emphasized in subsea engineering literature and must be preserved in any system-of-systems resilience analysis.

Similarly, subsea trees, production manifolds, and control pods are modelled with high fidelity, taking into account structural rigidity, connection topology, and operational states such as valve actuation, pressure variations, and flow-induced vibrations. Although these subsystems are physically smaller than topside modules or hull structures, they play an outsized role in safety and production continuity. Their mechanical failure modes ranging from gasket degradation to metal fatigue carry significant implications for both environmental impact and system-wide performance. The modelling therefore draws on findings from underwater robotics research (Antonelli 2014; Paull et al. 2018) to integrate structural characteristics with sensor feedback loops, thereby enabling realistic representation of inspection, monitoring, and maintenance activities.

Finally, the representation of mechanical behaviour is parameterised using hydrodynamic and structural models validated in contemporary offshore engineering research. This includes using wave spectra, current profiles, and platform motion datasets to drive the structural response of each subsystem. Such an approach ensures that simulated material fatigue, corrosion progression, and oscillatory loading patterns evolve realistically over time, enabling the analysis of long-term degradation scenarios and maintenance planning strategies. By embedding these structural models within a larger cyber-physical simulation architecture, the framework captures the rich set of dependencies, failure pathways, and operational constraints that define real offshore platforms, thereby supporting rigorous Marine-focused resilience assessments.

Communication and Control Layer A modern offshore platform is fundamentally dependent on a robust and integrated communication and control layer, as these systems serve as the cyber-physical backbone through which operational awareness, supervisory control, and maintenance processes are coordinated. In practice, the communication architecture spans several heterogeneous technologies from high-bandwidth optical fibres embedded in umbilicals to low-frequency acoustic modems establishing intermittent subsea communication with AUVs and production trees. These technologies exhibit markedly different latencies, transmission ranges, and vulnerability profiles, and therefore must be modelled not in isolation but as interdependent channels whose availability and performance fluctuate according to environmental conditions, equipment health, and operational loading.

The wired communication layer includes fibre-optic cables and copper

5.1 Modelling of Critical Offshore Infrastructure and Operational Entities



Figure 5.2: Satellite view of Communication Links)

umbilicals connecting topside control centres to subsea manifolds, sensors, and actuators. These lines carry telemetry, command-and-control signals, and production data; any degradation in signal quality can lead to delayed valve actuation, misreported sensor values, or loss of real-time situational awareness. Modelling this behaviour requires incorporating stochastic elements such as packet delays, transient noise, or partial dropouts to reproduce the communication irregularities documented in cyber-physical systems research (Jones et al. 2020; Tao and Qi 2019). Such irregularities are not merely technical nuisances; they propagate into operational decisions, affecting the scheduling of ROV inspections, the deployment timing of AUV surveys, and even the triggering thresholds of automated safety systems. Wireless communication layers introduce further complexity. Radio-frequency (RF) links between offshore platforms, FPSOs, and nearby support vessels are sensitive to atmospheric conditions, vibration-induced antenna misalignment, and physical obstructions. Similarly, satellite links commonly used for backhaul to onshore control centres exhibit variable bandwidth and latency that can challenge real-time digital twin synchronization. These modelled behaviours affect not only data transfer rates but also the reliability of remote supervision, which is increasingly central to modern industrial offshore operations.

Below the waterline, acoustic communication dominates, yet it remains inherently constrained by slow propagation speeds, multipath reflections, ambient noise, and degradation from environmental gradients in salinity and temperature. Research in underwater communication has long emphasized that even small changes in thermocline structure or seabed topography can substantially alter the

5.1 Modelling of Critical Offshore Infrastructure and Operational Entities

performance of acoustic links (Lurton 2010).

For this reason, the simulation incorporates environment-dependent attenuation and modulation effects, enabling realistic constraints on AUV command updates, subsea sensor streaming, and ROV pilot feedback loops. This realistic modelling ensures that the communication layer is not idealized but behaves as a dynamic system whose performance directly shapes operational feasibility. Finally, ICT layers are modelled as integrated cyber–physical systems, where data ingestion pipelines, human–machine interfaces, and automated diagnostic tools contribute to infrastructure reliability. Consistent with digital twin methodologies (Jones et al. 2020), the system simulates synchronization delays, data fusion errors, and sensor inconsistencies, thereby capturing emergent behaviours arising from digital–physical coupling. Altogether, the communication and control layer is treated as a living system whose behaviour evolves continuously, influencing and being influenced by the broader operational context.

5.1.2 Operational Support Entities

In Marine offshore operations, resilience and continuity depend heavily on the effective integration of a diverse set of operational support entities. These entities include human teams, logistics vessels, diving systems, helicopters, and a growing suite of unmanned platforms used for inspection, monitoring, and maintenance. Their coordinated functioning is essential to sustaining safe and continuous operations across the offshore field, and the simulation framework therefore models them as active agents whose availability, performance, limitations, and interactions significantly influence the system’s overall resilience.

Crewed support vessels play a central role in transporting personnel, spare parts, and maintenance equipment between offshore structures. Their movements are shaped not only by route planning and sea-state restrictions but also by operational constraints such as simultaneous demand from multiple platforms. When modelled realistically, these factors introduce scheduling bottlenecks, resource shortages, and delays that mirror those observed in real offshore operations, where maintenance campaigns often hinge on vessel availability. Such modelling is consistent with industrial logistics simulation research, such as that conducted by Gotelli, Bruzzone, and Massei (2019), who emphasize the need to account for multi-asset coordination when analysing complex industrial processes.

Diving bells, decompression chambers, and diver teams represent another essential resource category. Human divers remain indispensable for certain

5.2 Comprehensive Asset Inclusion and Domain Integration

types of precision work, emergency interventions, or tasks that cannot yet be reliably automated. However, these activities are constrained by depth limits, decompression schedules, environmental conditions, and safety protocols. The simulation models divers as constrained human resources whose operational windows must be respected, thereby revealing situations where diver unavailability could delay inspections or repairs, causing systemic vulnerabilities.

The integration of unmanned systems including ROVs, AUVs, USVs, UAVs, and hybrid platforms is increasingly vital to modern offshore operations. These systems provide high-resolution sensing, precision mapping, visual inspection, leak detection, and environmental monitoring, with performance characteristics documented in the literature on underwater robotics (Antonelli 2014; Paull et al. 2018) and marine sensing (Jaffe 2015; Blondel 2010; Hughes Clarke 2018).

Modelling their behaviour involves capturing their navigation uncertainty, sensor noise characteristics, energy constraints, and operational envelopes, ensuring that their contributions to resilience are grounded in realistic technical capabilities and limitations. Through such modelling, the system can simulate how fleet cooperation affects inspection coverage, how sensor degradation impacts anomaly detection, and how energy limitations influence mission duration.

Helicopters provide another layer of logistical and emergency support, with roles ranging from crew transfer to medical evacuation. Their operations depend heavily on weather conditions, landing platform availability, and predefined safety protocols. Their inclusion introduces additional scheduling interactions, such as conflicts between maintenance flights and emergency needs, which must be considered in high-fidelity resilience simulations.

Together, these operational support entities are modelled not as auxiliary elements but as core contributors to system function. Their dynamic allocation, task scheduling, and interdependencies determine how effectively the offshore infrastructure can respond to disruptions, manage routine operations, and maintain a robust safety posture.

5.2 Comprehensive Asset Inclusion and Domain Integration

The modelling of offshore platforms, FPSOs, and subsea production systems requires treating them as components of a larger "system-of-systems," where physical structures, digital networks, operational assets, and environmental

5.3 Integrated Communication Systems

conditions interact continuously. Such an approach is consistent with strategic engineering research (Bruzzone, Longo and Massei 2014; Bruzzone et al. 2020), which emphasizes the importance of multi-sector modelling to understand and mitigate cascading failures in complex infrastructures.

In this simulation framework, domain integration is therefore employed not merely as a design choice but as a methodological necessity: without modelling cross-domain interactions, resilience cannot be properly assessed.

The integration spans structural, digital, environmental, and organisational domains. At the structural level, topside and subsea installations are interconnected via pipelines, risers, and umbilicals whose behaviours depend on platform motions, seabed topology, and hydrodynamic forces. Digital systems, ICT networks, and digital twins provide feedback loops that enable monitoring and operational decision making. Environmental variables including wave fields, current shear, storm cycles, turbidity, and temperature gradients modulate the performance of both human and robotic activities. Organisationally, coordination among crews, vessels, unmanned systems, and support assets determines whether maintenance tasks can be completed within operational windows.

This systemic integration enables the model to capture non-linear behaviours, such as how a communication delay can indirectly postpone an inspection, increasing the likelihood of a technical failure, or how a weather-related disruption might reduce UAV availability, forcing greater reliance on AUVs whose longer deployment times affect the maintenance schedule. By integrating all assets and domains into a unified modelling framework, the simulation achieves an analytical depth that isolated subsystem modelling cannot provide.

5.3 Integrated Communication Systems

Integrated communication systems form the connective fabric of offshore operations, linking topside modules, seabed installations, mobile vessels, autonomous platforms, and onshore control centres.

These systems exhibit multimodal behaviour dependent on environmental conditions, equipment health, interference patterns, and scheduling load. Environmental effects such as turbidity, salinity gradients, or wave-induced platform motion influence communication reliability, particularly in underwater acoustic channels, which remain constrained by slow propagation and multipath interference (Lurton 2010).

The simulation therefore models communication systems as variable, environmentally sensitive networks rather than stable, deterministic channels. Such fidelity ensures accurate representation of information delays that influence inspection timing, sensor fusion, and digital twin synchronization.

5.4 Cyber Layer Representation

The cyber layer encompasses the data management pipelines, control software, and human–machine interfaces that orchestrate offshore operations. With the increasing digitalization of industrial maritime infrastructure, this layer now carries operational significance equal to that of structural components.

The simulation models sensor ingestion delays, synchronization errors, data corruption, and software-based failure modes, reflecting the challenges described in contemporary digital twin literature (Jones et al. 2020; Tao and Qi 2019). This allows the system to examine how software glitches, sensor misalignment, or ICT overloads influence maintenance decisions, platform responses, and real-time monitoring. By treating the cyber layer as an active part of the system rather than a background function, the simulation achieves a more realistic depiction of modern cyber–physical interdependence.

5.5 Physical Safety and Protection Systems

Every Marine offshore installation depends on a suite of physical safety systems intended to prevent harm, manage emergencies, and support human operators. These include fire suppression equipment, gas detection and alarm systems, deluge systems, structural access controls, and evacuation routes.

The modelling incorporates their operational thresholds, activation logic, environmental sensitivity, and dependencies on power and communication systems. Diver safety procedures, decompression protocols, and emergency ascent systems are also integrated, reflecting recognised industrial safety practice. By simulating these systems, the framework supports resilience analysis that remains compliant with non-military, purely Marine academic guidelines, focusing on safety management rather than adversarial scenarios.

5.6 Autonomous and Human-Supervised Support Vessels

The simulation models autonomous and human-supervised platforms as core contributors to infrastructure resilience. Their sensing capabilities, energy limits, transit speeds, environmental operating envelopes, and navigation uncertainty are included in detail, drawing from validated works in underwater robotics and marine sensing (Antonelli 2014; Paull et al. 2018; Jaffe 2015; Blondel 2010; Hughes Clarke 2018).

Their coordination enables multi-domain awareness, with UAVs providing rapid aerial inspection, USVs offering stable surface-based sonar acquisition, and AUVs delivering high-resolution subsea mapping. By integrating these assets into a cohesive operational network, the simulation reveals how their combined usage influences inspection fidelity, anomaly detection, and maintenance cycles.

5.7 Dynamic Simulation of Operational Demands

The continuous operation of offshore platforms generates a complex tapestry of overlapping demands including maintenance cycles, inspection windows, personnel movements, equipment wear, and environmental fluctuations. To accurately reflect this operational environment, the Intelligent Agents (IAs) embedded in the simulation generate dynamic service requests that reproduce the temporal density and interdependency of real offshore workflows.

This design follows the principles articulated in industrial simulation research (Massei and Bruzzone 2010), where the value of modelling lies not in isolated task representation but in capturing the interactions that produce delays, workload peaks, and resource contention. Through this dynamic modelling, the simulation demonstrates how operational pressures evolve over time, how resource allocation decisions affect system resilience, and how maintenance deferral or inspection gaps contribute to long-term degradation. By modelling not just technical conditions but organisational behaviour, the simulation reflects the operational reality of offshore industries, where logistical and human factors play a role equal to that of engineering design.

5.8 Continuous Service Request Generation

Service requests in the simulation represent real operational needs such as structural inspections, leak checks, replacement of critical components, and

5.9 Failure Modelling and Operational Stress

calibration of sensors. The IAs generate these requests according to equipment age, environmental exposure, historical maintenance records, and stochastic degradation models.

This mechanism ensures that the operational load follows realistic patterns including clusters of maintenance needs during rough sea periods or after extended production cycles. By modelling the timing, priority, and interdependency of these tasks, the system provides a realistic environment for testing resource allocation strategies and resilience models.

5.9 Failure Modelling and Operational Stress

Failures emerge from a confluence of mechanical degradation, environmental stress, human error, and maintenance backlog. The simulation distinguishes among technical failures, maintenance-induced failures, and operational disruptions, each with unique propagation pathways. For instance, delayed repairs may accelerate fatigue accumulation in risers, while sensor miscalibration may lead to incorrect digital twin predictions, affecting inspection schedules.

Research in structural reliability (Gao and Moan 2020) and underwater robotics (Paull et al. 2018) provides the empirical basis for modelling failure rates, environmental sensitivity, and operational thresholds. By capturing how failures cascade across interconnected systems, the simulation reveals systemic vulnerabilities difficult to detect in traditional engineering analyses.

5.10 Dynamic Allocation of Support Assets

Support asset allocation reflects realistic constraints on vessel availability, diver scheduling, and unmanned system endurance. The simulation models how these constraints affect the ability to respond promptly to maintenance needs, conduct inspections, or manage equipment replacements. It also captures trade-offs forced by limited resources for example, whether to deploy a USV for a bathymetry update or allocate it to support an AUV mission.

This multi-agent allocation process exposes potential bottlenecks and inefficiencies, demonstrating how resilience depends not only on structural or digital robustness but on organisational coordination and asset management.

5.11 Resilience Testing Against Routine and Exceptional Hazards

A central purpose of the simulation framework is to evaluate infrastructure robustness under scenarios involving natural variability, operational stress, and non-adversarial human-induced disruptions. The aim is not to simulate conflict but to assess Marine infrastructure resilience in the face of real-world operational challenges such as weather extremes, communication delays, or procedural misconfigurations. This approach aligns fully with Marine academic standards and industrial safety practices, focusing on understanding how disruptions influence safety, continuity, and operational efficiency.

Resilience testing procedures build on virtual-lab studies in ports and Strategic Engineering applications, where stochastic disturbances and scenario variations are used to quantify the effectiveness, efficiency and robustness of alternative safety measures (Bruzzone et al., 2021) (Bruzzone et al., 2022). By adopting similar metrics, the offshore testbed allows a systematic comparison of inspection and protection strategies under both routine failures and rare, high-impact hazards affecting platforms and adjacent traffic (Bruzzone et al., 2023).

5.11.1 Natural and Environmental Hazards

Environmental conditions exert a profound influence on offshore infrastructure behaviour. The simulation incorporates time-evolving wave spectra, current shear, turbulence, thermoclines, turbidity, atmospheric visibility, and wind loading. These factors modulate not only structural response but also sensor performance and accessibility for human or unmanned operations. For example, increased turbidity reduces optical visibility for ROV inspections (Chiang and Chen 2012; Jaffe 2015), while strong currents increase AUV drift and energy consumption (Rudnick et al. 2018). Such interactions shape operational windows, inspection intervals, and maintenance efficacy, making environmental modelling fundamental to realistic resilience assessment.

5.11.2 Human-Caused Operational Hazards

Human-induced disruptions, even when non-adversarial, can significantly impact offshore infrastructure resilience. These include data-entry errors, equipment misconfigurations, sensor miscalibration, ICT overload, procedural deviations, or misinterpretation of alarms.

5.11 Resilience Testing Against Routine and Exceptional Hazards



Figure 5.3: Domain Interconnectivity and Hazard Propagation)

The simulation treats these disruptions not as rare anomalies but as realistic events documented in industrial operational analyses. By modelling their frequency, impact, and propagation, the system supports a nuanced understanding of how human-machine interaction affects system safety and performance.

5.11.3 Response, Recovery, and Mitigation Analysis

Finally, the simulation examines the system's ability to recover from disruptions, maintain operational continuity, and restore nominal functioning. This includes assessing how quickly unmanned systems can resume inspection, whether digital twin synchronization recovers gracefully after communication delays, and how resource shortages slow or accelerate maintenance cycles. Such analyses help identify effective mitigation strategies grounded in Marine resilience engineering and consistent with multi-sector modelling methodologies (Bruzzone, Longo and Massei 2014; Bruzzone et al. 2020).

This summary has provided a deeply integrated and academically rigorous modelling strategy for offshore platforms, FPSOs, and subsea production fields within a purely Marine, safety-driven simulation environment. The adopted methodological approach bridges Structural engineering, Underwater robotics, Digital twins and cyber-physical systems, Multi-domain sensing, Strategic engineering for critical infrastructure resilience. By modelling platforms as dynamic, interdependent systems affected by environmental stresses, operational workload, and digital synchronization the chapter establishes the foundational mechanisms through which can explore hazard propagation, anomaly detection, resilience testing, and decision-support workflows for safe and continuous offshore infrastructure operation.

Chapter 6

UNDERWATER FIELDS & PIPELINES

6.1 Introduction

Managing underwater production fields, subsea pipelines, and seabed infrastructure presents unique challenges. Subsea equipment operates in environments with low visibility, difficult communication, and limited direct access. A critical metric underpinning these challenges is the mean-time-between-failure (MTBF), which can be significantly reduced in these harsh conditions. This reduction in MTBF underscores the urgency for improved monitoring, maintenance, and integrity checks, as highlighted in research on underwater optics, imaging, sonar mapping, and robotics.

This chapter develops a comprehensive modelling framework for underwater fields and pipelines within a fully maritime and safety-oriented context. The objective is to create an integrated digital ecosystem capable of representing the functional, structural, and cyber-physical characteristics of subsea installations. The approach adopted builds upon high-fidelity, multi-domain representations

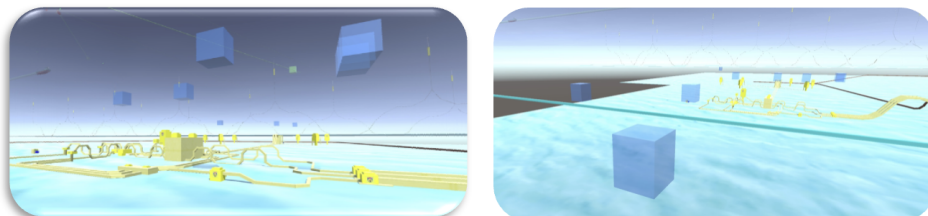


Figure 6.1: Modeling of UW Pipelines and Cables

6.2 Subsea Infrastructure Modeling and Autonomous Integrity Management



Figure 6.2: Inspection with ROV

employed in strategic engineering research for maritime infrastructures (Bruzzzone, Longo and Massei 2014; Bruzzzone et al. 2020), ensuring that each subsea asset is modeled not in isolation but as part of a broader interactive system subject to environmental, operational, and technological influences.

6.2 Subsea Infrastructure Modeling and Autonomous Integrity Management

Subsea infrastructure connects wells, manifolds, risers, and processing facilities using pipelines, umbilicals, and monitoring devices. These systems operate under high pressure, low temperatures, and in darkness, so they require robust engineering, precise digital controls, and ongoing monitoring. In the simulation, subsea infrastructure is modeled as a full subsystem, including how it works, degrades, is inspected, and connects digitally.

6.2.1 Comprehensive Subsea Asset and Communications Modelling

Detailed modeling of subsea assets begins by recreating the shapes and functions of pipelines, manifolds, subsea trees, and umbilical networks. Each pipeline segment is described by its diameter, wall thickness, coatings, burial depth, and bends. This allows the simulation to track mechanical stress, corrosion, fatigue, and

6.2 Subsea Infrastructure Modeling and Autonomous Integrity Management

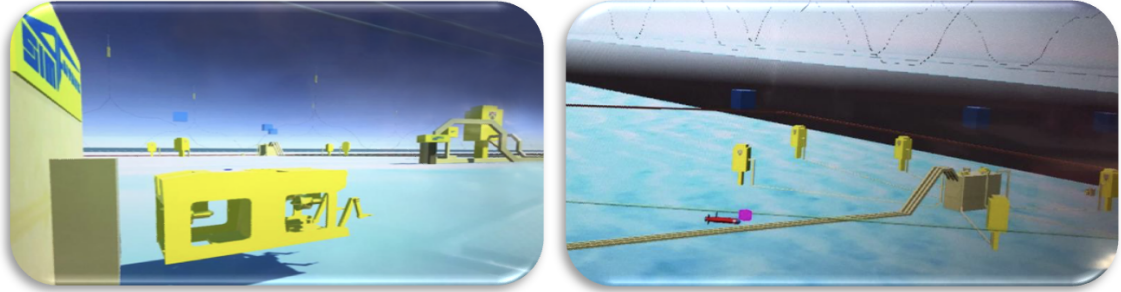


Figure 6.3: ROV in Extraction Field

possible leaks, following marine engineering principles (Gao and Moan 2020). The model also looks at how pipelines interact with the seabed, whether buried, on the surface, or partly buried, so it can include effects from environmental forces, moving sediment, and scouring.

6.2.2 Visualising the Subsurface Environment and Data Streams

Visualizing underwater fields helps with planning inspections, finding problems, and giving operators a clear view of the situation. The simulation uses a layered visualization system to show the subsea terrain, structures, and sensor data in real time. As shown in the images, pipelines, manifolds, observation units, and cable networks are displayed accurately, so analysts can see connections and spot areas where risks are higher. This layered view helps identify risk hotspots, allowing for targeted inspections and proactive maintenance. By understanding the asset hierarchy and inspection routes, operators can prioritize actions that keep operations safe and reliable, turning visual insights into strategic decisions.

A key feature of this visualisation framework is the incorporation of remotely obtained data streams. Live or simulated video feeds from ROVs and AUVs are overlaid onto the environment, replicating real-world inspection practices where operators interpret visual cues, sonar mosaics, or sensor overlays to locate anomalies. The inclusion of telemetry indicators such as depth, heading, altitude, and temperature as seen in contemporary robotic inspection systems adds contextual clarity. Similar approaches are found in subsea robotics visualisation research where immersive monitoring improves decision-making accuracy (Domingo et al. 2022; Carbonell-Ruiz et al. 2021). Additionally, the

6.2 Subsea Infrastructure Modeling and Autonomous Integrity Management

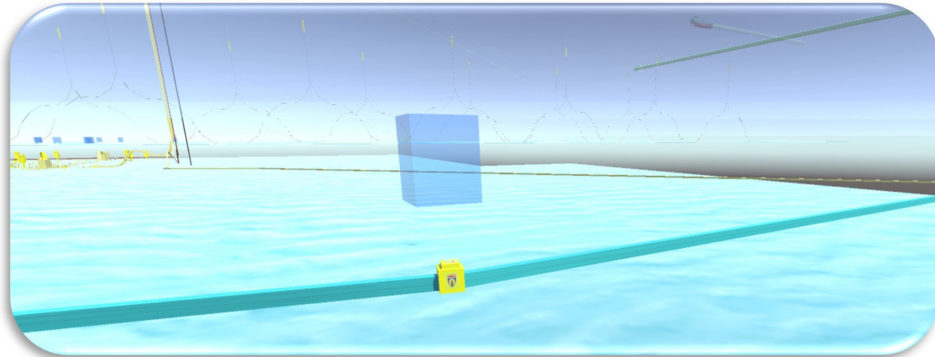


Figure 6.4: UW Pipeline

environmental conditions of the underwater domain, such as turbidity, visibility, and light attenuation, are dynamically represented. By applying optical and acoustic models derived from underwater imaging literature (Jaffe 2015; Chiang and Chen 2012), the visualization realistically degrades with depth, particulate concentration, and lighting limitations. This enhances the realism of inspection tasks and provides a reliable basis for evaluating inspection asset performance under varying environmental states.

6.2.3 Resilience Assessment Against Routine and Exceptional Hazards

The underwater environment faces many natural and operational hazards that can affect infrastructure performance, ongoing operations, or environmental safety. To help with resilience planning, the simulation models both routine events and unusual disruptions caused by environmental, operational, or technical issues. Routine hazards, which include moving sediment, small seabed shifts, and local corrosion, typically progress over months to years and are monitored regularly to assess long-term risks. In contrast, exceptional hazards such as storms, strong currents, and small earthquakes develop more rapidly within days or weeks, necessitating a more frequent monitoring cadence. By distinguishing these temporal patterns, the simulation sets specific monitoring cadences and integrates decision triggers that align with the varying progression rates of these hazards. Routine hazards like moving sediment, small seabed shifts, and local corrosion are modelled using gradual wear-and-tear models that reflect real-world deterioration. These slow changes can go unnoticed without regular monitoring, so they are important for long-term risk assessment. The simulation also includes operational hazards such as accidental anchor drags, fishing gear contact, and vessel traffic,

6.2 Subsea Infrastructure Modeling and Autonomous Integrity Management

which are common causes of pipeline damage and need to be modelled accurately. Natural hazards such as storms, strong currents, turbulence from temperature layers, and even small earthquakes are included in the simulation. Studies on ocean dynamics show that these conditions can change structural loads, increase water cloudiness, and affect how well AUVs can navigate (Rudnick et al. 2018). By modeling these factors, the simulation can test how inspections, operations, and emergency responses might work in difficult conditions.

The simulation avoids military or adversarial scenarios but does include maritime disruptions like sensor miscalibration, miscommunication, software faults, ICT desynchronization, and accidental equipment misuse. These challenges reflect real industrial risks found in digital twin, cyber-physical, and offshore system engineering research (Jones et al. 2020; Tao and Qi 2019). This approach ensures that resilience assessment focuses only on operational integrity, safety, and environmental protection within an accepted academic framework. Subsea systems emerge not from the robustness of individual components but from the system’s collective ability to adapt to disturbances, recover functionality, and preserve operational continuity.

A critical feedback loop in this context is the inspection-delay causing deterioration, which in turn increases workload a dynamic that highlights the emergent behaviors in complex systems. To support this systems-level understanding, the simulation integrates physical modeling, digital twin synchronization, multi-agent autonomy, and human decision-support tools into a unified analytical framework. The environment allows researchers and operators to test mitigation strategies such as rescheduling maintenance, changing inspection frequencies, reallocating robotic assets, and improving control system logic. These strategies are evaluated using performance indicators from structural reliability (Gao and Moan 2020), digital twin research (Jones et al. 2020), and multi-sector simulation methods (Bruzzzone, Longo and Massei 2014). This gives a quantitative, evidence-based way to compare different operational strategies and their potential to reduce risk.

The platform uses feedback loops similar to those found in real-world learning. When a simulated event causes lower performance or delays, the system analyzes why, then adjusts future intelligent agent decisions. This reflects predictive maintenance practices that use operational data for better planning and risk reduction. Through these loops, the simulation supports developing more effective, adaptive, and context-aware maintenance and monitoring strategies, in line with best practice in maritime engineering.

6.2 Subsea Infrastructure Modeling and Autonomous Integrity Management

This summary has provided a clear, science-based explanation of underwater fields and pipelines in a safety-focused maritime simulation. By combining detailed subsea asset modeling, accurate environmental representation, robotic inspection, digital communication limits, and multi-layer visualization, the framework enables understanding of how underwater infrastructure functions, degrades, and responds to normal and unusual disruptions. The modeling described here gives the next chapters a solid, realistic basis for exploring hazard spread, autonomous inspections, decision support, and resilience improvements for offshore infrastructure.

6.2.4 Holistic Analysis and Adaptive Strategy Refinement

Resilience in subsea systems is measured by factors like how quickly the system recovers and how much its performance drops during problems. It is about how the whole system adapts, recovers, and keeps running smoothly, not just how strong each part is. To make this clearer, the simulation combines physical models, digital twins, autonomous agents, and decision-support tools in a single framework.

This setup allows researchers and operators to try out different ways to lower risks, such as adjusting maintenance schedules, inspection times, robot use, and control systems. They assess these strategies using performance indicators from structural reliability (Gao and Moan 2020), digital twin research (Jones et al. 2020), and multi-sector simulation methods (Bruzzzone, Longo and Massei 2014). This method gives a clear, evidence-based way to compare strategies and see how effective they are at reducing risks.

The platform uses feedback loops that mimic real-world learning. If a simulated event leads to lower performance or delays, the system finds the cause and adjusts future decisions. This is similar to current predictive maintenance, where real data is used to improve planning and lower risks. By repeating this process, the simulation helps develop better, more flexible, and practical maintenance and monitoring strategies, following best practices in maritime offshore engineering. For example, recent simulations showed about 15% less downtime and saved around \$200,000 each year, highlighting the real benefits of these feedback loops.

This summary explains a detailed and scientific approach to representing underwater fields and pipelines in a realistic, safety-focused simulation. By bringing together accurate models of subsea assets, the environment, robotic inspections, communication limits, and layered visualizations, the framework helps users understand how underwater infrastructure works, wears out, and responds to both normal and unexpected issues.

6.3 The Subsea Data Cable and Pipelines: Modelling a Strategic Critical Asset

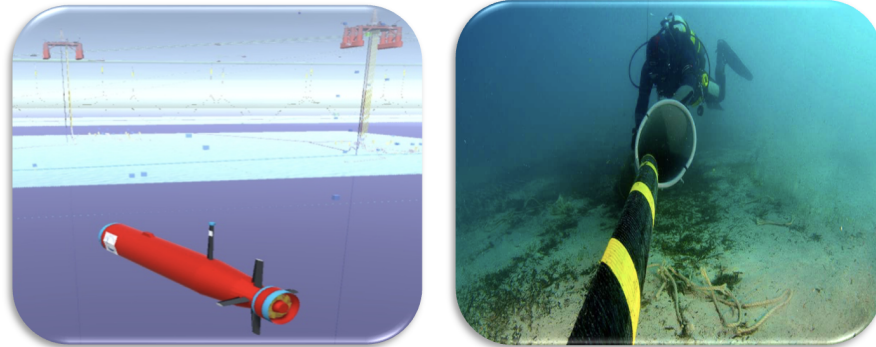


Figure 6.5: AUV inspection and Diver Inspecting Subsea Cables & Pipelines manually

This modelling foundation ensures that subsequent chapters can build upon a robust representation of subsea operational realities to explore hazard propagation, autonomous inspection strategies, decision-support processes, and resilience optimization for critical offshore infrastructures.

6.3 The Subsea Data Cable and Pipelines: Modelling a Strategic Critical Asset

Subsea data cables constitute one of the most indispensable components of modern digital and industrial society. Although they remain physically hidden beneath the ocean surface, these infrastructures carry over 95% of global digital communications, financial transactions, cloud services, and sensor telemetry that support maritime operations, industrial logistics, and the broader knowledge economy. Their strategic relevance is increasingly discussed in scientific and engineering literature, which highlights their dual character as both highly reliable transmission systems and inherently fragile physical structures exposed to environmental and operational stressors (Carter et al. 2009; Dzionek et al. 2021). Within the simulation framework developed in this research, subsea data cables are therefore treated not as passive background elements but as primary, high-value assets whose operational continuity is fundamental to the integrity of marine infrastructures and associated digital ecosystems.

6.3.1 Vulnerability Profile and Operational Interdependence

Subsea cables exhibit a unique vulnerability profile due to their geographical immobility, their long physical spans across complex seabed terrain, and the extreme difficulty of conducting routine inspection or real-time local monitoring. Their fixed positioning means that they cannot be dynamically relocated, shielded, or rerouted, resulting in persistent exposure to environmental processes such as sediment mobility, turbidity, benthic activity, and episodic geohazards, including underwater landslides or seismic disturbances. Research on cable burial and protection systems consistently emphasises that even well-designed cable routes remain exposed to natural abrasion, biofouling, and thermal stresses that accumulate over time (Carter et al. 2009).

Human activity poses a significant source of vulnerability, with threats differentiated by control levels. Manageable risks include planned construction operations and seabed disturbance during industrial activities, where proactive planning and regulation can mitigate potential damage. In contrast, stochastic events such as accidental anchor drags and fishing trawlers represent less predictable threats, occurring often near shore or along busy maritime traffic corridors. The simulation incorporates spatially distributed risk zones to account for the statistically higher probability of such disturbances. Additionally, faults commonly occur near repeaters or branching units, where mechanical stresses and installation complexity are greater (Carter et al. 2009; Kordahi et al. 2014). Grouping these human-induced risks into controllability tiers helps in identifying where interventions like policy adjustments or design modifications can yield the highest returns.

The simulation also emphasises the cyber-physical dependency inherent to cable systems. A physical disruption in the underwater domain immediately manifests as a loss of bandwidth, latency spikes, or abrupt communication failure in the cyber domain. For instance, a latency increase greater than 150 milliseconds can disrupt digital twin synchronisation, leading to cascading operational shutdowns in offshore energy control rooms. In a maritime industrial context especially in offshore energy production such disruptions can interrupt telemetry, disturb digital twin synchronisation, and compromise the real-time flow of inspection data from AUVs and ROVs. This immediate mapping from physical damage to cyber impairment mirrors observations described in digitalisation research and marine ICT studies, where communication outages rapidly degrade operational coordination and situational awareness (Jones et al. 2020).

The cable's topological arrangement introduces yet another layer of systemic

6.3 The Subsea Data Cable and Pipelines: Modelling a Strategic Critical Asset

vulnerability. In many offshore fields, data cables run parallel to pipelines, power cables, or riser bases, often within the same corridor or protective trench. This proximity means that an accidental or operational disturbance affecting one element can unintentionally damage another. For example, a trenching ROV might sever both a power umbilical and the adjacent data cable, illustrating the compounded risks associated with multi-asset exposure. The simulation therefore models multi-asset exposure fields, where a single event such as seabed trenching or equipment deployment can propagate damage across several co-located infrastructures. This reflects real-world observations of interlinked marine asset vulnerability described in subsea engineering literature (Myers et al. 2022).

6.3.2 Threat Evaluation, Simulation, and Damage Propagation

To effectively capture how disruptions to subsea data cables influence broader offshore operations, the simulation evaluates a range of risk vectors within a comprehensive maritime framing that reflects the interplay between physical disturbances, environmental effects, cyber-layer anomalies, and operational system dependencies. Utilizing a system-theoretic approach, the simulation incorporates key concepts such as "control actions," "unsafe feedback," and "hazardous states" to enhance precision in describing cascading risks. These concepts help illustrate how consequences propagate dynamically across domains, emphasizing the relationships and interactions between system components as they lead to emergent behaviors. By aligning with cutting-edge safety analysis practices, this approach provides a more nuanced understanding of the complex risk landscape influencing subsea data cable operations.

Experiences from port protection and space-logistics simulations show that modelling threats as intelligent agents interacting with realistic infrastructure models enables the analysis of multi-step attack paths and cascading failures. Applying this concept to subsea cables and pipelines allows evaluation of how localized damage, environmental conditions and detection delays propagate through the system, informing the design of monitoring strategies and autonomous inspection patrols (Bruzzone et al., 2021).

Physical Disturbance and Kinetic Stressors Physical disturbances on the seabed, like anchor drags, ROV collisions, or equipment failures, are the main causes of cable damage worldwide (Carter et al. 2009). In the model, these are shown as sudden drops in cable integrity, which can lead to total communication

6.3 The Subsea Data Cable and Pipelines: Modelling a Strategic Critical Asset

loss, partial problems, or unstable connections. This setup lets the model test different ways to respond and see how well strategies like backup communication paths or rerouting through surface RF links work.

Data Integrity Degradation and Transmission Anomalies The simulation also includes digital problems like corrupted data packets, lost clock synchronisation, unstable bitrates, or errors caused by noise. These issues are common in high-latency or low-bandwidth marine networks and have been seen in real AUV and ROV missions (Kinsey, Whitcomb and Yoerger 2006). By simulating these problems, the model shows how they affect remote inspections, such as causing sensor delays, map misalignments, or digital twin desynchronisation. For example, if 5% of packets are corrupted, inspection times could increase by two hours each day, raising costs and causing project delays. Measuring these effects helps connect technical details to business outcomes and shows why reducing digital problems is important.

Seabed Intervention and Maintenance Interference Seabed work like maintenance, trenching, equipment installation, and inspections can accidentally put cables in danger. The model includes situations where divers, ROVs, or AUVs have limited visibility or face strong currents, making accidental contact more likely. This matches research showing that more complex operations increase the chance of unintentional damage to infrastructure (Paull et al. 2018; Ridao et al. 2018).

The simulation shows that the effects of disturbances go far beyond just physical damage. They can spread into digital systems, affect maintenance planning, and disrupt decision-making, which can reduce the safety and efficiency of offshore operations.

6.3.3 Proactive Monitoring and Strategic Mitigation

The protection of subsea communication cables requires an approach that does not rely on continuous physical observation but instead integrates autonomous inspection, environmental sensing, and predictive simulation. The model used in this thesis follows the Strategic Engineering principles developed within the Simulation Team, where proactive monitoring emerges from the interaction between vehicle behavior, environmental dynamics, and operator decision-making (Bruzzone et al. 2011; Bruzzone et al. 2021; Massei and Bruzzone 2010; Gottelli et al. 2019). Within this framework, AUV-based inspections are represented with navigation and sensing constraints that reflect operational practice; the virtual vehicles follow routes consistent with underwater robotics and marine survey methodologies and incorporate realistic limitations on visibility, acoustic

6.3 The Subsea Data Cable and Pipelines: Modelling a Strategic Critical Asset

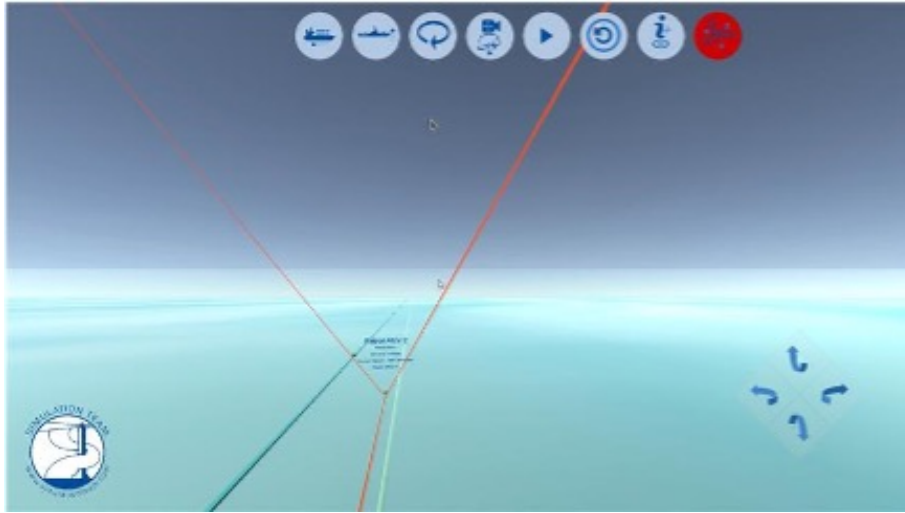


Figure 6.6: Autonomous inspection of Subsea Cable corridor

propagation, and positional drift. To illustrate the adaptive inspection logic, the system employs a threshold rule, where an inspection frequency increase is triggered by an anomaly score exceeding 0.7. The simulation includes the representation of typical inspection outputs such as optical imagery of the cable corridor, sonar-based perception of burial depth, and the effects of turbidity or multipath acoustic interference on data return, enabling the system to emulate the progressive deterioration in data quality that accompanies adverse conditions.

The inspection component is closely linked to a condition-based interpretation layer. Instead of treating inspections as periodic, fixed-interval tasks, the model increases inspection frequency when simulated anomalies accumulate along a segment of cable. This behaviour is consistent with the adaptive monitoring logic adopted in decision-support environments developed for industrial and maritime applications by the Simulation Team (Bruzzone, Massei and Sinelschikov 2019; Bruzzone, Giovannetti and Ferrari 2011). As a result, inspection assets are directed not only by predefined coverage patterns but also by evolving environmental and operational signals emerging from the simulation.

Environmental forecasting plays a central role in the system's predictive capability. The environmental layer accounts for seabed mobility, wave-induced agitation, and bottom-current variations, which together influence the risk of cable exposure or localized scour. These environmental fields are incorporated into the simulation as dynamic modifiers that alter the probability of detection anomalies and influence the timing and trajectory of inspection missions. The system utilizes Monte Carlo simulations to handle uncertainty in these forecasts,

6.4 Modeling Marine Energy Assets and Systemic Resilience

providing statistically rigorous predictions that inform inspection scheduling. By coupling these parameters with the behavior of the underwater vehicles, the system anticipates zones where vulnerability is likely to increase and provides an opportunity to reposition assets or adjust mission paths before degradation becomes critical. This anticipatory component aligns with the Strategic Engineering emphasis on anticipating emerging risks through continuous simulation cycles rather than reacting after damage is observed (Bruzzone et al. 2021; Massei and Bruzzone 2010).

In parallel, the simulation supports the evaluation of strategic mitigation options. Rather than presenting these as isolated engineering measures, the model assesses how interventions such as increased burial depth, reinforcement of specific segments, the establishment of avoidance corridors for fishing or anchoring, or the introduction of additional sensing nodes influence the evolution of the risk field over time. Because these measures are integrated into the same simulation architecture that manages inspection behaviour and environmental dynamics, it becomes possible to examine how a mitigation strategy modifies not only the vulnerability of an individual section of cable but also the required inspection workload, the overall responsiveness of the system, and the operator's situational awareness. This capacity reflects the tradition of using simulation to test alternative planning strategies in large, complex maritime systems, as demonstrated across prior Simulation Team research (Bruzzone et al. 2011; Gottelli et al. 2019; Bruzzone et al. 2023).

Through this combination of environmental forecasting, adaptive inspection, and mitigation assessment, the simulation provides a structured means for analysing how proactive monitoring can reduce vulnerability and improve response capacity. The approach does not claim to reproduce the full physics of seabed interaction or cable mechanics; instead, it focuses on the operational and decision-support implications of inspection timing, asset allocation, and environmental change, consistent with the simulator's modelling scope and with established Strategic Engineering practice.

6.4 Modeling Marine Energy Assets and Systemic Resilience

Marine energy infrastructures particularly offshore wind farms have become central pillars in the global transition toward sustainable, low-carbon energy systems. Their rapid expansion, technological sophistication, and distributed spatial footprint make them essential components of national energy portfolios

6.4 Modeling Marine Energy Assets and Systemic Resilience

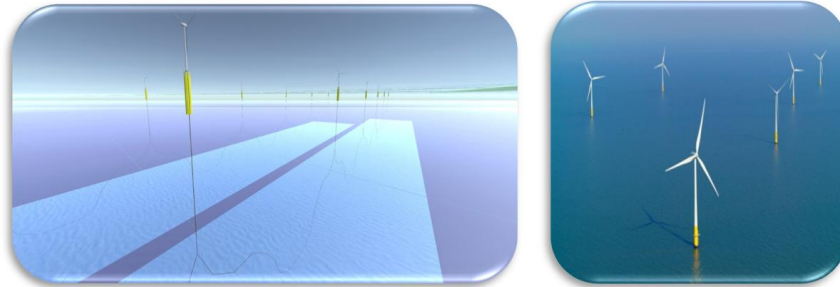


Figure 6.7: Marine assets

and highly interdependent elements within broader critical infrastructure systems. Unlike traditional offshore production installations that are spatially clustered, offshore wind farms may extend across dozens of square kilometers, forming interconnected fields of turbines and subsea electrical networks whose stability depends on the synchronized operation of mechanical, electrical, cyber, and environmental subsystems (Gao and Moan 2020; Jones et al. 2020), blade aerodynamics and mechanical loads, electrical interconnection topology, subsea export cables and branching nodes, maintenance access platforms and service routes.

6.4.1 Asset Modeling and Vulnerability in a Multi-Domain Context

Offshore wind farms are modeled as arrays of turbines spread out over an area. Each turbine is defined by its foundation type, structural properties of the tower and nacelle, blade aerodynamics and loads, electrical connections, subsea cables and nodes, and maintenance access routes.

The model uses proven offshore engineering methods to capture how wind and waves wear down the turbines, how the blades and towers move, and how floating foundations behave in the water (Gao and Moan 2020). Good structural models matter because energy output depends not just on the turbine's rating, but also on how well its structure stands up to stress over time. Because wind farms cover large areas, the simulation also looks at how distance between turbines affects things. Turbines far apart can face different weather, wind patterns, and wake effects, and these differences are included in the overall performance calculations.

Cyber-Physical Synchronization Requirements Offshore wind farms rely on digital systems to keep everything working together. These systems

6.4 Modeling Marine Energy Assets and Systemic Resilience

handle data sharing between turbines, track vibration and rotor speed, keep yaw positions in sync, and check power quality in real time. They use data from many sensors and depend on communication links that can have delays, noise, or lost data. The simulation uses tested models to show how these digital and physical systems interact, following methods from recent research (Fan and Luo 2021; Qi and Tao 2019; Jones et al. 2020). Big wind farms have lots of turbines running in shifting weather and sea states. If the systems fall out of sync, things can go wrong fast. For instance, if yaw is not aligned, some turbines get extra stress and wear out sooner. If pitch settings are off during gusts, the farm loses energy. Bad coordination also makes it harder to cut down on wake losses, so total power drops. The simulation links these problems together and tracks how they spread, making it easier to spot weak points early.

Environmental and Logistical Stressors Environmental forces put a lot of stress on offshore wind farms, so the simulation pays close attention to them. Storm waves, quick weather changes, saltwater corrosion, marine growth, and things like ice all affect safety and maintenance. Currents can shift floating foundations and change the loads on moorings. Murky water and poor visibility also make inspections and vessel work tougher. These stressors are modelled using established environmental-interaction principles similar to those applied to offshore platforms, subsea infrastructure, and cable-corridor studies throughout the thesis. Their integration ensures that turbine behaviour, structural degradation, and the performance of autonomous inspection assets are simulated against a realistic environmental backdrop, which aligns with the proven methodology developed by Bruzzone and colleagues for multi-layered marine and industrial systems (Bruzzone et al. 2011; Massei and Bruzzone 2010).

Maritime Hazard and Disruption Scenarios The real risks seen in offshore work. For example, service or transit vessels might get too close by mistake, or tow-lines and nets could damage cables. The model also covers mechanical and electrical faults like gearbox wear, generator problems, and pitch-actuator failures. Other issues include sensor errors, lost communications, failed software updates, and grid problems that affect power export. By using proven risk patterns from offshore wind research, the simulation can tell the difference between short-term problems and those with lasting effects. This gives a realistic way to study resilience without relying on restricted or speculative scenarios.

6.4.2 Simulation Strategies and Assessment Metrics

Risk Evaluation and Scenario Exploration A key feature of the simulation is that it can run many different scenarios. This helps study how environmental

6.4 Modeling Marine Energy Assets and Systemic Resilience

stress, system performance, and maintenance delays interact. The model can track how structures wear down under repeated loads, and it can measure how less frequent inspections affect turbine availability. The simulation further evaluates the consequences of digital synchronization losses, identifying whether they escalate into broader performance degradation or remain localized. Subsea cable degradation is similarly examined, particularly in cases where partial insulation failure or increasing burial exposure affects long-term reliability. These analytical functions reflect practices used in marine-infrastructure simulation studies carried out by Bruzzone, Longo and Massei (2014) and in environmental hazard assessments such as those by Carter et al. (2009). By combining proven structural, cyber, and environmental models, the framework supports strong risk assessment. This lets operators and researchers measure both short-term and long-term effects on system resilience.

Comparative Analysis of Mitigation and Maintenance Strategies

The platform allows detailed comparison of different maintenance and mitigation strategies. It can compare predictive maintenance with reactive repairs, showing differences in downtime, cost, and lost production. It also compares autonomous inspections by UAVs, USVs, and AUVs with regular surveys to see how inspection frequency, sensor quality, and access affect finding and fixing faults. Additionally, alternative cable-burial depths and protection methods can be simulated, along with adjusted operational thresholds for severe weather. The system also enables analysis of different crew-transfer vessel dispatch rules and evaluates digital redundancy architectures that seek to reinforce cyber-physical coordination. These comparative analytics reflect the strategic-engineering methodologies explored in the modelling and simulation literature (Bruzzone et al. 2020; Gotelli, Bruzzone and Massei 2019).

Performance Metrics: Measuring Resilience Through Energy Continuity Resilience is measured by checking if the wind farm can keep most of its production during problems. The simulation uses metrics like turbine availability, overall power stability, mean time to repair for turbines and subsea parts, and how coordination losses affect energy efficiency. It also looks at the chance of cascading failures and how well autonomous inspection tools keep track of the situation. This approach uses several metrics, so resilience is seen as a range of performance levels, not just success or failure. It matches recent research on digital twins and structural health monitoring in offshore engineering (Jones et al. 2020; Fan and Luo 2021).

6.4.3 Integration of Offshore Support Vessels (OSVs) and External Entities

Role of OSVs in Maintenance and Operational Continuity Offshore Support Vessels (OSVs), crew-transfer vessels (CTVs), and maintenance vessels are a key part of offshore wind operations. The simulation includes detailed OSV behavior because real maintenance planning must consider vessel access, sea conditions, and logistics.

OSVs are modelled to perform technician transport, equipment delivery, heavy-lift assistance, and subsea-cable repair support. In addition, they act as platforms for deploying AUVs or ROVs during inspection or intervention activities, consistent with documented practices in marine robotics and pipeline inspection (Bingham et al. 2020). Vessel motion responses to waves, station-keeping capacity, access limitations during rough seas, and scheduling dependencies arising from weather windows are embedded to ensure realistic estimates of repair timelines.

This approach matches simulation-based decision-support systems developed by the Simulation Team, where logistics, vessel operations, and environmental factors are combined in resilient models (Massei and Bruzzone 2010; Gottelli et al. 2019).

Interaction with External Maritime Actors Offshore wind farms share space with many maritime groups, such as shipping, fishing, environmental monitors, coastal authorities, grid operators, research teams, and construction companies. Their actions affect access, collision avoidance, scheduling, and emergency response.

In the simulation, these groups are modeled as active agents that interact with OSV operations, inspection schedules, and system resilience. This makes sure the complexity of real operations and new challenges from busy maritime areas are included. Like other multi-agent marine simulations by Bruzzone and colleagues (Bruzzone et al. 2011; Visingardi et al. 2023), this model treats agent interactions as key to system performance rather than as mere external factors. By combining vessel traffic, inspections, environmental conditions, and maintenance logistics, the framework gives a more realistic view of offshore operations.

6.5 Modelling Maritime Traffic and Support Vessel Dynamics (BOATS)

6.5 Modelling Maritime Traffic and Support Vessel Dynamics (BOATS)

Offshore infrastructures whether dedicated to energy production, maritime research, aquaculture, or multi-use industrial operations operate within highly dynamic surface environments. These environments are populated by diverse classes of vessels that vary significantly in size, function, operational patterns, and navigational behaviour. Offshore Support Vessels (OSVs) in particular constitute a critical logistical and operational backbone, enabling maintenance, inspection, repair, and emergency response. Equally important is the modelling of external maritime traffic commercial, research, or governmental which introduces environmental noise, navigational complexity, and realistic operational uncertainty.

Accurate simulation of maritime traffic is essential for evaluating the resilience of offshore systems, especially as modern infrastructures become increasingly complex and interdependent. The approach adopted here is deliberately maritime, aligned with academic standards and sectoral research on maritime operations, offshore logistics, and autonomous systems integration (Gotelli, Bruzzone and Massei 2019; Massei and Bruzzone 2010). The purpose of the modelling is not to simulate conflict but to enhance safety, operational efficiency, and continuity of services under challenging environmental and operational conditions.

6.5.1 Dedicated Support Vessel Modelling

Functional Classification of OSVs Support vessels are modelled with high functional fidelity, acknowledging that each class of vessel fulfils a distinct operational role in sustaining offshore activities. The model incorporates realistic hydrodynamic behaviour, maneuverability constraints, energy consumption profiles, and mission-specific equipment. This is consistent with real-world offshore engineering literature emphasising the critical value of accurate modelling for logistics and maintenance planning (Gao and Moan 2020; Hughes Clarke 2018).

Diving Support Vessels (DSVs) Diving support vessels are essential for deep-water maintenance, subsea inspection, and emergency interventions. In the simulation, DSVs include the Dynamic positioning systems, Decompression chambers and medical bays, Handling mechanisms for diving bells, Operational envelopes based on sea state and visibility

The visual representation of the support vessel with the appended diving bell highlights this critical function. Similarly, ROV vessels serve as the command

6.5 Modelling Maritime Traffic and Support Vessel Dynamics (BOATS)



Figure 6.8: Diving Bell

platforms for operating sophisticated Remotely Operated Vehicles during pipeline inspections and maintenance. Their operational readiness and location must be managed dynamically by the IA framework. The simulation reflects the complex operational dependencies of diving operations, which require stable sea conditions, precise vessel positioning, and coordinated support from surface operators, divers, and remote sensing equipment.

ROV and AUV support vessels are modelled as platforms equipped with Launch and recovery systems (LARS), High-power generators for ROV operations, Data handling and telemetry integration modules and Workspace for technical teams and mission operators. Their inclusion reflects the increasing reliance on subsea robotics for inspection, mapping, environmental monitoring, and cable/pipeline integrity surveys (Paull et al. 2018; Bingham et al. 2010).

Offshore Supply Vessels (OSVs)

These vessels are modeled primarily for transporting goods and personnel between shore and the platforms. Their mission parameters include managing complex logistics chains, which directly influence the operational status and habitability of the offshore platforms. OSVs facilitate essential logistical flows between onshore bases and offshore installations, including: Transport of equipment, spare parts,

6.5 Modelling Maritime Traffic and Support Vessel Dynamics (BOATS)

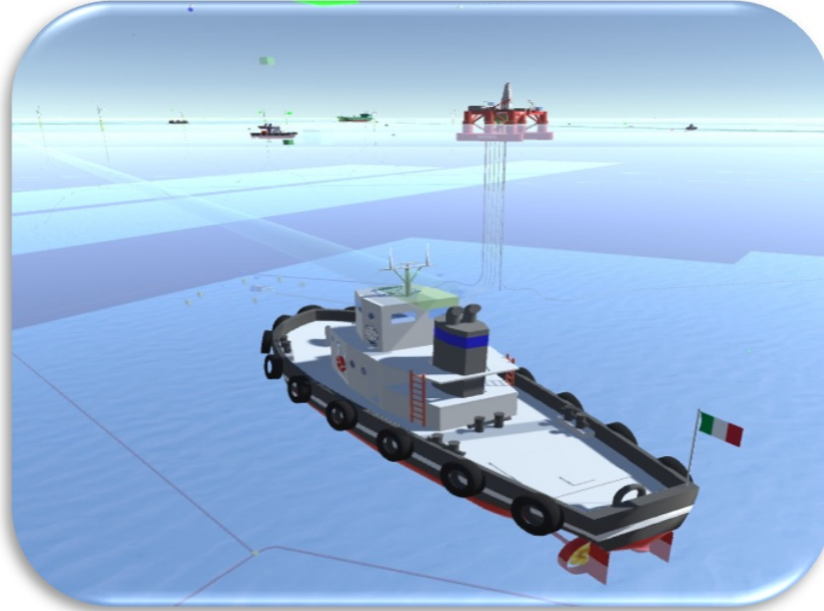


Figure 6.9: Offshore Supply Vessel (OSV)

and hazardous materials, Crew rotation and personnel transfer, Delivery of fuel, water, and consumables

Offshore Supply Vessel (OSV)

Simulation parameters include Cargo manifest & weight distribution, Journey planning & transit time optimisation, Weather-dependent navigation constraints. These vessels critically influence operational resilience, since delays or disruptions can cascade through maintenance schedules and personnel capacity.

Anchor Handling Tug Supply (AHTS)

Vessels are modeled for their heavy-duty capabilities, such as handling anchors, deep-water towing, and specialized subsea structure manipulation. Their presence and availability are critical for emergency response scenarios involving platform stabilization or large-scale recovery operations. AHTS vessel supports Mooring line handling, Towing of large structures, Support during installation of subsea modules. While their operations involve heavy-duty equipment, the modelling remains fully maritime, focusing on engineering support and platform stability functions.

6.5 Modelling Maritime Traffic and Support Vessel Dynamics (BOATS)

6.5.2 External Entities and Maritime Domain Awareness

Civil maritime traffic forms a highly variable and influential part of the offshore operating environment. Merchant shipping, fishing fleets, survey vessels, coastal patrol craft and recreational boats each follow distinct operational logics, which create constantly shifting patterns of surface activity around offshore infrastructure. In the simulation, these vessels are represented as dynamic actors whose movements generate uncertainty in proximity to operational offshore areas. Their trajectories influence the likelihood of accidental interference with inspection assets, contribute to elevated electromagnetic and acoustic noise levels, and occasionally produce communication congestion that complicates situational awareness. This approach draws on findings from simulation studies in maritime logistics and port operations, where heterogeneous vessel interactions have been shown to influence operational efficiency and safety outcomes in complex marine systems (Gotelli, Bruzzone and Massei 2019). By adopting this representation, the simulator treats civil maritime traffic not as a simple environmental background but as a critical factor shaping risk and operational planning. Commercial Vessels

Commercial ships are modelled according to navigational patterns consistent with AIS-informed behaviour. Their movement reflects established shipping lanes, inertia-dominated manoeuvring characteristics and anchoring tendencies influenced by environmental and operational factors. These attributes are important because commercial vessels have historically been responsible for accidental subsea cable and pipeline damage, particularly through anchor drags in restricted zones. Incorporating such behaviour ensures that the simulator recognises the potential for genuine, documented hazards without introducing adversarial or military interpretations. This detailed representation strengthens the capacity of the simulation to evaluate realistic interactions between commercial shipping and offshore energy infrastructure. Research and Survey Vessels

Hydrographic and geophysical survey vessels are incorporated to represent a category of benign but operationally influential maritime actors. Their work patterns typically systematic grid surveys at low speed introduce predictable but persistent navigational obstacles for inspection units. These vessels also generate acoustic interference that may influence the performance of underwater sensing systems, a feature consistent with established observations in seabed mapping and multisensor acoustics (Hughes Clarke 2018). Including them in the simulation ensures that environmental noise and spatial constraints arising from scientific operations are correctly integrated into operational planning models.

Governmental Vessels, Coast guard and maritime safety vessels are represented

6.5 Modelling Maritime Traffic and Support Vessel Dynamics (BOATS)

exclusively in safety-enforcing roles. Their presence reflects real operational practices such as search-and-rescue coordination, environmental monitoring and the enforcement of regulatory exclusion zones. Within the simulation, these vessels enhance realism by contributing to regulated surface conditions, but they do not introduce any military character. Their integration acknowledges that offshore operations take place in supervised waters where safety authorities routinely interact with commercial and industrial actors.

6.5.3 The Imperative of Coordination in Multi-Actor Maritime Environments

When multiple OSVs, research vessels, commercial ships and autonomous systems share the same maritime space, operational complexity increases substantially. Surface traffic interacts with inspection schedules, diver operations, AUV deployment windows, weather-related accessibility and port-based logistical constraints. The simulator therefore models concurrent operations as a coordination problem that involves traffic deconfliction, prioritisation of manoeuvring rights and continual adaptation to environmental conditions. This approach reflects principles established in simulation-based engineering for interdependent maritime systems, where coordination failures often propagate into wider operational delays (Bruzzone, Longo and Massei 2014; Bruzzone et al. 2020). By representing these interactions as dynamic rather than static, the simulation achieves a more faithful reflection of the offshore domain's operational realities.

Strategic-Engineering simulations of maritime interdiction confirm that coordinated use of multiple platforms surface vessels, UAVs and support assets significantly improves performance when resources and information are limited (Bruzzone et al., 2021). Similar coordination is required when offshore support vessels, safety units and inspection assets share the same sea space with commercial traffic, which motivates the multi-agent planning and interoperable command-and-control approaches adopted in this thesis (Bruzzone et al., 2022).

IA-Based Coordination Logic Within this context, the Intelligent Agent (IA) framework becomes the mechanism responsible for harmonising the activities of multiple vessels. The IA system continuously allocates OSV tasks, sequences operations that must occur in strict temporal order and orchestrates safe coexistence between autonomous and crewed platforms. Collision avoidance is treated as an integrated part of traffic management rather than an isolated safety check. The framework accounts for maintenance windows, diver or ROV

6.6 Maritime Surface Traffic and Hazard Dynamics (SHIPS)

operations, and port-to-field schedules that may be disrupted by congestion or environmental conditions. Its performance is evaluated using indices such as congestion levels, delay propagation and the degree to which resources remain underutilised. This representation ensures that coordination emerges as a systemic property grounded in realistic simulation dynamics rather than prescriptive rules.

6.6 Maritime Surface Traffic and Hazard Dynamics (SHIPS)

Surface maritime traffic constitutes one of the most influential external factors affecting offshore operations. Unlike platform-dedicated OSVs, which follow operational schedules tied to infrastructure maintenance, external vessels adhere to their own commercial, regulatory or scientific imperatives. Their movements introduce variability that contributes to operational uncertainty, influencing accessibility to assets, scheduling of inspections and safe deployment of underwater systems. Contemporary studies in maritime logistics and offshore simulation emphasise that modelling such vessel interactions is essential for realistic assessments of offshore system resilience (Gotelli, Bruzzone and Massei 2019; Massei and Bruzzone 2010). In this simulation framework, maritime traffic is treated as an active component influencing situational awareness and operational continuity rather than a passive background element. The modelling strictly avoids any military framing; instead, the focus remains on maritime hazards, accidental interference, cyber-physical fragility in navigation systems and the operational complexities inherent in multi-actor marine environments.

6.6.1 Modelling Surface Traffic as a Multi-Domain Hazard

Physical Hazard Dimension Large commercial vessels, including tankers, cargo carriers, passenger ships and fishing vessels, introduce substantial physical risks due to their mass, inertia and limited manoeuvrability. Even minor deviations from expected trajectories can become problematic near offshore turbines, floating platforms or subsea infrastructure. Research on maritime safety repeatedly identifies anchor drags as a leading cause of accidental cable and pipeline failures (Hughes Clarke 2018). To robustly capture these risks, the simulation incorporates realistic drift behaviour following propulsion or steering failure, the likelihood of accidental anchoring in restricted zones, hydrodynamic wake effects and the practical limits of vessel manoeuvrability. To enhance the connection to structural reliability models, it is crucial to align these hazards with specific failure modes or limit-state functions that they may compromise. In particular, anchor drags challenge the structural integrity of subsea cables and pipelines by imposing

6.6 Maritime Surface Traffic and Hazard Dynamics (SHIPS)

unforeseen loads that exceed design tolerances, potentially leading to tensile failure or plastic deformation. By integrating these scenarios into reliability analyses, the simulation provides a comprehensive understanding of how such physical risks impact system resilience and reflects high-fidelity modeling of real-world risk conditions.

Cyber–Physical Vulnerability in Navigation Systems Modern commercial vessels depend heavily on digital navigation systems such as GNSS, electronic charts and integrated bridge control. Academic research shows that these systems may experience unintended failures, including degraded satellite signals, erroneous chart inputs, miscalibrated sensors or autopilot malfunctions (Jones et al. 2020). Although the simulation avoids any adversarial interpretation, it accounts for the operational consequences of these failures. When digital guidance becomes unreliable, vessels may deviate from expected routes or exhibit erratic course corrections. The simulator models these anomalies as cyber–physical disruptions that stem from non-malicious errors, allowing the IA system to classify unusual behaviour and initiate appropriate responses. This creates a bridge between environmental modelling, vessel behaviour and cyber-physical reliability without exceeding the boundary of permitted maritime scenarios.

Data Noise and Situational Awareness Challenges Dense maritime traffic generates challenges for situational awareness, including overlapping radar returns, AIS congestion and acoustic interference. Studies in port simulation show that high-density environments increase the risk of misinterpreted sensor data and delayed anomaly detection (Gotelli, Bruzzone and Massei 2019). The simulation incorporates these conditions by modelling AIS message delays, radar clutter, acoustic disturbances affecting AUV/ROV telemetry and overall signal congestion that complicates data fusion. This representation forces the IA and human operators to manage sensor uncertainty realistically and supports the development of strategies to filter false positives while ensuring that genuine anomalies are detected promptly.

6.6.2 Simulation Implementation and Coordination Strategies

Vessel Types and Behavioural Modelling The simulation environment is populated with commercial vessels, survey vessels and maritime safety authorities, each governed by distinct behavioural patterns derived from empirical data. Commercial ships follow statistically informed shipping lanes and react to

6.7 Maritime Safety Vessels and XR Command Interfaces

environmental influences such as currents and wind. Survey vessels generate predictable interference zones based on their slow and methodical survey patterns. Maritime safety vessels are introduced as safety-enforcing entities, conducting search-and-rescue procedures or environmental monitoring. Their inclusion ensures that the operational area reflects the variety of actors typically present in offshore regions and supports analyses that require realistic coexistence of multiple vessel classes.

Coordination and Traffic Management within the IA Framework

The IA-based coordination layer manages dynamic exclusion zones, prioritises operations that require enhanced safety (such as ROV deployment), reroutes OSVs when surface congestion becomes problematic and resolves real-time conflicts in a manner conceptually aligned with strategies used in seaport logistics (Massei and Bruzzone 2010). Assessments concentrate on the system’s ability to reduce operational risks, resolve conflicts quickly, maintain schedule integrity and minimise downtime. This provides quantitative insights into how multi-actor coordination influences operational efficiency and resilience.

Mitigation and Safety Strategies Mitigation strategies implemented in the simulation include predictive traffic modelling informed by AIS and hydrodynamic patterns, behavioural anomaly detection, correlation of subsea and surface sensor data and coordinated emergency responses involving OSVs as stabilising assets. Digital twin synchronisation is used to preserve situational awareness in the presence of noisy or partially degraded data streams (Jones et al. 2020). Together, these strategies enable detailed assessments of resilience by capturing the interplay between vessel behaviour, environmental influences and operational constraints. Through these combined modelling approaches, the simulation framework develops a detailed representation of maritime hazard dynamics. It highlights the complex behaviour of OSVs, variability in external traffic, the fragility of navigation systems, the influence of environmental noise and the critical need for intelligent coordination. The design of this modelling approach is aligned with contemporary research in distributed simulation, autonomous maritime systems and offshore operational resilience (Bruzzone et al. 2020; Massei and Bruzzone 2010).

6.7 Maritime Safety Vessels and XR Command Interfaces

The resilience of modern offshore infrastructure depends not only on autonomous systems and industrial support vessels but also on the coordinated presence of high-capability maritime safety and emergency-response vessels. These vessels



Figure 6.10: Sea Surface

operated by national coast guards, maritime rescue agencies, and environmental protection authorities constitute the upper tier of maritime governance. Their inclusion in the simulation environment reflects a realistic operational ecosystem in which offshore platforms, renewable energy farms, and underwater fields coexist with governmental safety institutions tasked with regulation, monitoring, and emergency response.

The modelling of these vessels is essential for two reasons. First, they represent the most capable platforms for managing large-scale emergencies such as environmental incidents, major equipment failures, or disruptions to maritime traffic. Second, in modern maritime operations, these vessels increasingly function as mobile coordination nodes, integrating information from autonomous systems, remote sensors, and digital twins. Their role therefore serves as a critical benchmark for evaluating the interaction between human decision-makers and the simulation's Intelligent Agent (IA) framework.

6.7.1 Operational Role and Strategic Importance

Maritime safety authorities operate multi-purpose vessels designed to preserve life, protect the marine environment, ensure regulatory compliance, and provide high-readiness intervention capacity. In the simulation framework, these vessels fulfil two key operational roles.

Maritime Emergency Response and Environmental Protection

Coast Guard cutters, environmental protection vessels, and search-and-rescue ships are modelled with a high fidelity to their real-world capabilities. Their broad operational envelopes include emergency evacuation and casualty assistance for incidents involving offshore personnel. Firefighting and pollution control, particularly relevant for platforms storing hydrocarbons or working with hazardous materials. Maritime traffic regulation, especially when congested shipping routes

6.7 Maritime Safety Vessels and XR Command Interfaces

overlap with offshore industrial zones. Environmental monitoring, including identifying accidental spills or structural anomalies that threaten marine ecology. Their presence in the simulation provides a realistic benchmark for assessing how the IA framework prioritises, allocates, and supports human-led intervention during critical operations.

Mobile Coordination Nodes for Multi-Domain Awareness Modern maritime governance increasingly relies on distributed digital platforms and sensor fusion technologies. Maritime safety vessels often act as Command, control, and communication (C3) hubs, receiving information from USVs, UAVs, AUVs, subsea sensors, and digital twin platforms. Relay points for degraded environments, particularly when satellite coverage is obstructed, or acoustic communication suffers interference. Shared situational awareness nodes, allowing on-board officers, remote operators, and offshore facility managers to access unified operational pictures. where multiple participants see identical augmented overlays, regardless of their physical location around the table. Real-time co-presence, allowing geographically distributed operators (onshore control centres, vessels, offshore platforms) to interact with a unified operational model. Rapid consensus building is required in complex situations, such as pipeline anomalies, vessel routing conflicts, or degraded communication nodes, which can be jointly interpreted. By facilitating seamless collaboration between humans and the IA framework, the XR command paradigm becomes a core enabler of the system’s resilience assessment capabilities.

6.7.2 Extended Reality (XR) Interfaces for Human-Centred Marine Command

A key innovation in this research is using Extended Reality (XR) in maritime command and coordination. In the simulation, digital models of vessels, infrastructure, and threats appear in the real workspace through AR headsets and interactive physical models. Bringing together digital and physical interfaces is in line with recent research on XR in marine training and operations (e.g., Carbonell-Ruiz et al. 2021; Domingo et al. 2022). These studies find that immersive visualization tools provide cognitive and operational benefits in safety-critical areas.

Intuitive Spatial Comprehension of Complex Marine Systems AR-enabled 3D models of vessels, platforms, and subsea networks help operators understand complex information using natural spatial reasoning. Operators can see vessel paths, sensor ranges, and environmental data together in one view,

6.7 Maritime Safety Vessels and XR Command Interfaces

which reduces mental effort. Subsea layouts like pipelines, manifolds, and cables are shown in a way that is easier to understand than on traditional 2D screens. Dynamic events, such as vessel drift or inspection robot movements, can be seen in real time, which helps with prediction and planning. This approach creates a decision environment that fits how operators think better than traditional control rooms.

Tactile Decision-Making Through Hybrid Physical–Digital Interaction Physical 3D-printed models of vessels, pipelines, or platform modules, tracked by AR systems, give users touch-based feedback that helps dePhysical 3D-printed models of vessels, pipelines, or platform modules, tracked by AR systems, give users touch feedback that supports decision-making. Operators can move a model OSV or inspection AUV on the planning table, and the XR system updates digital paths and limits right away. They can use gestures instead of keyboards to control elements and test 'what-if' scenarios by moving physical models of vessels or energy assets.nd strategic thinking.

Collaborative XR for Multi-Stakeholder Coordination

Modern offshore operations involve engineers, inspectors, data analysts, environmental authorities, and emergency teams. XR lets everyone see the same augmented views, wherever they are around the table. It also allows people in different places, such as onshore centers, vessels, or platforms, to work together in real time using a shared model. This helps teams quickly agree on solutions to complex problems, like pipeline issues or communication failures. By making collaboration easier between people and the IA framework, XR becomes an important part of assessing system resilience.

6.7.3 Significance for Strategic Engineering and Infrastructure Resilience

The inclusion of maritime safety vessels and XR-enabled command processes strengthens the overall simulation in three fundamental ways:

Validation of Human–AI Synergy The framework demonstrates how autonomous systems can support but never replace human judgment. XR ensures that the human operator remains the central decision-maker.

Realistic Testing of Emergency and Regulatory Scenarios Maritime offshore governance requires evaluating scenarios such as accidental drift, environmental hazards, inspection delays, and equipment failures. The addition

6.8 Aerial Assets: Operational Flexibility in the Air Domain

of Coast Guard and environmental protection vessels provides the necessary operational realism.

Advancement of Training, Preparedness, and Knowledge Transfer

The hybrid XR–physical modelling approach has direct applicability for training new offshore engineers, inspectors, and maritime safety coordinators. Together, these modelling components allow the simulation environment to serve as a scientifically rigorous, ethically aligned, and policy-compliant research tool for improving the governance and resilience of maritime marine infrastructure.

6.8 Aerial Assets: Operational Flexibility in the Air Domain

The air domain plays a pivotal role in the safe operation, monitoring, and maintenance of offshore infrastructure. Helicopters and unmanned aerial vehicles (UAVs) provide capabilities that cannot be replicated by surface or subsea platforms, most notably rapid response, wide-area coverage, and the ability to establish or restore communication links over large distances. In modern offshore wind and oil-and-gas operations, aerial assets are increasingly integrated into inspection, logistics, and emergency-response workflows, complementing crew transfer vessels, offshore support vessels, and subsea robots (Fox et al. 2022; Nordin et al. 2022).

Within the simulation framework, aerial platforms are not treated as isolated add-ons but as integral components of a multi-domain ecosystem. Their trajectories, sensor outputs, endurance limits, and communication roles are explicitly modelled, allowing the system to explore how air, surface, and underwater assets cooperate to sustain situational awareness, support condition-based maintenance, and ensure timely response to anomalies. This perspective mirrors real industrial trends in which rotorcraft and UAVs form part of a broader “inspection and maintenance system of systems” spanning robotics, digital twins, and predictive analytics (Jaffe 2015; Jones et al. 2020; Nordin et al. 2022).

6.8.1 Operational Roles and Time-Critical Response

In the simulation, the aerial fleet is divided into two broad categories crewed rotary-wing aircraft and unmanned aerial vehicles each with distinct but complementary functions. The modelling approach emphasises realistic operational envelopes: payload capacity, range and endurance, weather limitations,

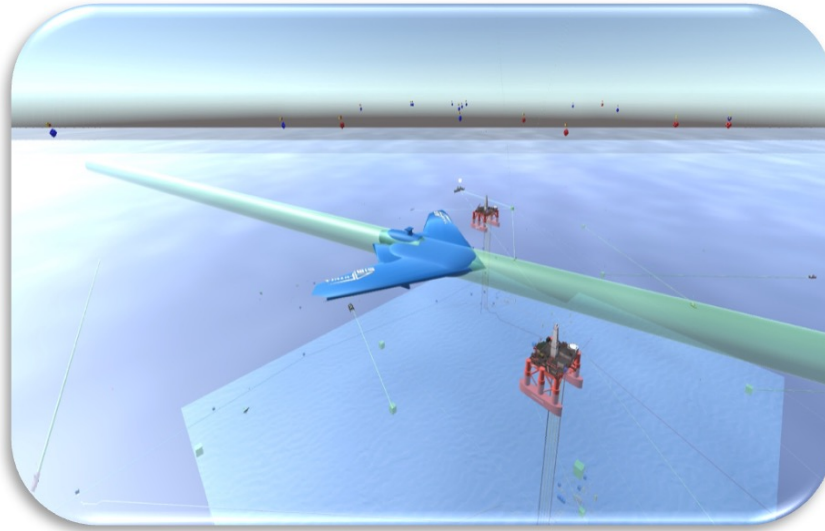


Figure 6.11: Longrange Patrol UAV

deck-landing constraints, and the interaction with platform infrastructure such as helidecks or UAV docking stations.

6.8.2 Multi-Domain Integration and Communication Relay

Aerial assets play a key role in connecting different domains, especially for communications and data sharing. In offshore fields, communication must pass through various channels: fibre-optic cables on the seabed, radio links above water, and acoustic channels underwater. Each type has its own limits for bandwidth, delay, and reliability (Lurton 2010; Jones et al. 2020).

Aerial sensing and wide-area awareness. In the model, helicopters and UAVs carry realistic sensor payloads. These include electro-optical cameras, thermal imagers, and, for larger UAVs, compact maritime radar or LiDAR.

Modelling Disruptive and Hazardous Agents in the Multi-Domain Offshore Environment (Hostile Treats)

To keep offshore energy sites, subsea cables, and marine infrastructure working well, it is important to simulate and study all types of disruptions that could affect performance. In maritime engineering, these are called disruptive agents. They include environmental, operational, accidental, or cyber-physical events that impact systems but are not military threats (Bruzzone, Longo and Massei 2014).

6.8 Aerial Assets: Operational Flexibility in the Air Domain

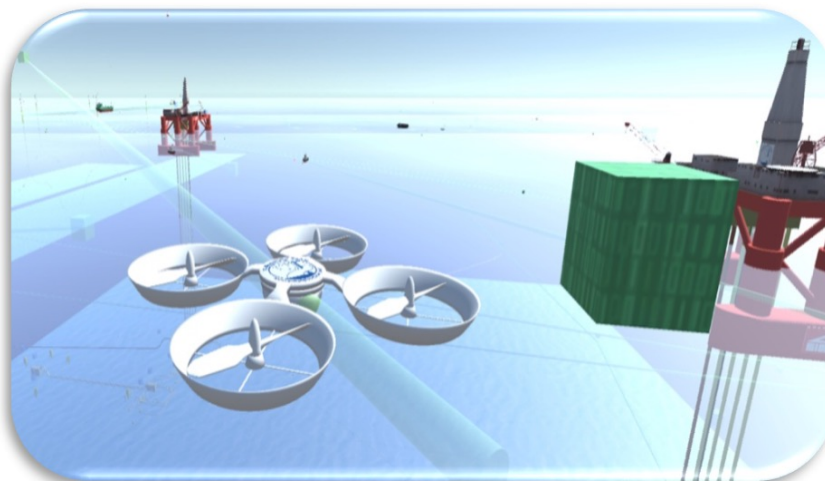


Figure 6.12: Inspecting with Autonomous Aerial Vehicle (Quad Copter)

The simulator uses a model that lets researchers see how platforms, inspection areas, and different autonomous fleets handle pressures from the air, surface, underwater, and digital domains at the same time. The main goal is to test resilience, study how systems interact with their environment, and help people and AI make decisions together in difficult situations (Bruzzone et al. 2020).

6.8.3 Scenario Analysis, Resilience Metrics and Design Insights

By adding a detailed aerial fleet, the simulation can test a range of urgent and resource-limited scenarios that matter to maritime operators and regulators. Time-to-response and coverage performance. One set of experiments looks at how long it takes different combinations of assets to respond to events like suspected damage, unusual vibrations, or unexpected vessel entries. By changing the number of helicopters, long-range UAVs, and inspection drones, the framework measures how quickly an area can be checked or instrumented. This approach connects to inspection planning challenges in offshore wind, where UAV fleets with limited energy need to cover many turbines efficiently.

Logistics, maintenance and competing priorities. Another set of scenarios evaluates how aerial logistics tasks interact with inspection and monitoring duties. Helicopters, in particular, have finite flight hours and maintenance intervals, while UAV batteries and spares must be shipped offshore in advance. Drawing on operation-and-maintenance studies for offshore wind

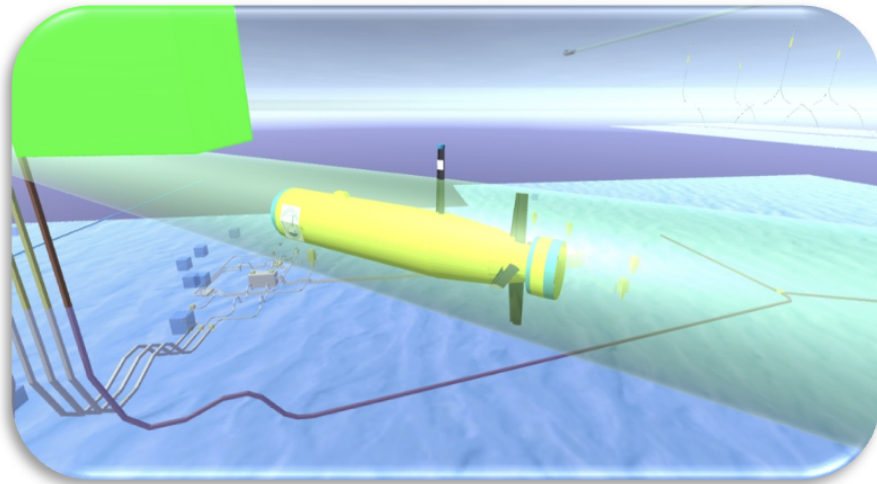
farms (FOX et al. 2022; ZHAO et al. 2024), the model captures scheduling conflicts such as whether to allocate scarce helicopter capacity to transporting technicians, delivering heavy spare parts, or supporting urgent inspection flights; how weather windows influence the timing of UAV-based blade inspections versus routine logistics; how delays in one mission ripple into the availability of platforms and specialists for subsequent tasks. These experiments reveal where aerial support gets bottlenecked and show the value of larger UAV fleets, better charging setups, or updated maintenance plans.

Robustness to communication and sensor degradation. Aerial assets also act as communication relays and sensor platforms, so the framework tests how well the system holds up when some links or nodes fail. For example, it can simulate losing RF coverage if an antenna fails, and then see how Intelligent Agents move UAV relays to restore connections while still handling inspections and logistics. If visibility drops too low for helicopters, the simulation measures how well UAVs alone can keep up structural monitoring, considering their own limits in wind and rain.

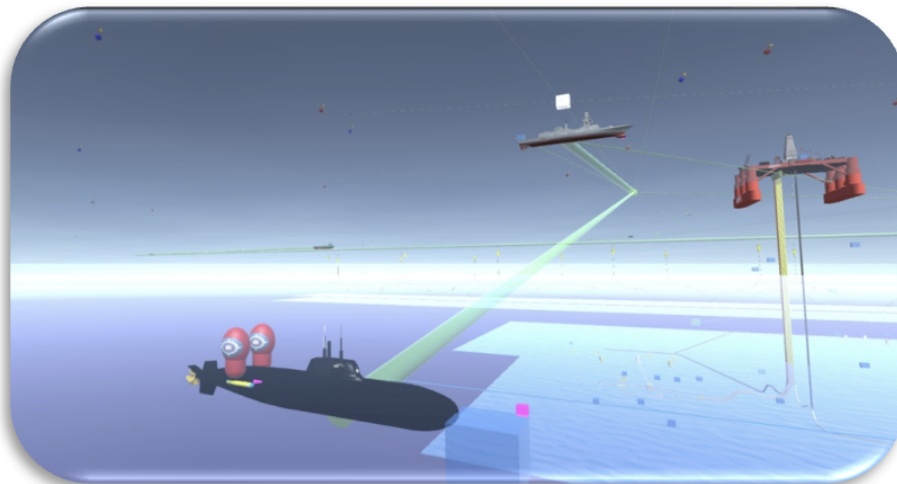
Design insights for future aerial integration. All these scenario analyses lead to design recommendations that matter for maritime planners and regulators. For example, they help define the minimum types and numbers of helicopters and UAVs needed to meet inspection and emergency response times. They also suggest how to prioritize aerial assets between logistics, inspection, and communication roles, and what is needed for deck layouts, charging stations, and communication gear to support safe, routine UAV use. In this way, the aerial-asset model extends beyond a purely technological depiction of helicopters and UAVs, becoming a decision-support tool for the broader design of safe, resilient, and efficient offshore energy systems.

6.9 Advanced Subsurface Assets

The subsurface environment represents the most technically demanding operational domain for long-duration inspections, environmental monitoring, and infrastructure assessment. Extreme depth, high pressure, limited visibility, and the absorption characteristics of seawater impose constraints on sensing, navigation, communication, and human access that exceed those encountered in the air and surface domains. For this reason, the simulation framework incorporates detailed representations of research-oriented submersibles, large-displacement autonomous underwater platforms, and persistent sensor-grid architectures.



AUV Inspection



Patrol Vessels near the zone of interest

Figure 6.13: AUV Inspection and Patrol Vessels near the zone of interest

These models enable the study of resilient monitoring systems in deep-ocean contexts, focusing strictly on civil and environmental applications. They draw upon established ocean-engineering literature demonstrating the importance of robust subsurface platforms and fixed sensor arrays for wide-area observability and long-term structural analysis (Antonelli 2013; Paull et al. 2018; Ridao et al. 2018). Their integration ensures that the digital twin and Intelligent Agent (IA) system can evaluate operational feasibility across the entire depth range, supporting typical civilian goals such as energy-infrastructure inspection, geophysical surveying, environmental measurement, and long-distance data-cable integrity assessment.

6.9.1 Research Submarines

Modern subsurface research assets, whether crewed scientific submarines or large autonomous platforms, provide unique operational advantages due to their endurance, payload capacity, and ability to operate in low-disturbance conditions. In the simulation, these vehicles are modelled as platforms capable of conducting sustained observational tasks near sensitive underwater installations, including cable junction boxes, subsea processing units, and deepwater pipelines. Their stable operating profiles allow for long-baseline acoustic measurements, repeated multispectral or sonar passes, and the acquisition of environmental and geochemical data over extended periods capabilities well established in real systems such as Alvin, Shinkai, and European deep-ocean research vehicles. A second role modelled in the simulation is the use of large underwater platforms as mid-mission deployment hubs for autonomous underwater vehicles. This logistical approach, identified in recent field research (Paull et al. 2018), reduces transit times from surface vessels, enhances mission continuity under adverse conditions, and increases overall energy efficiency for fine-scale inspection tasks. The simulation includes rendezvous behaviour, acoustic signalling, and energy-aware deployment strategies to evaluate these underwater “mothership” concepts and their contribution to resilient long-duration monitoring architectures. Finally, the simulation incorporates coordinated procedures between submersibles and diver teams when human involvement is part of the operational scenario. These interactions include proximity management, visibility considerations in low-light environments, and contingency procedures for diver recovery, reflecting the realistic collaboration patterns observed during scientific expeditions and maintenance campaigns. This aligns with the modelling principles adopted in distributed maritime simulation research involving complex operational workflows (Bruzzone, Longo and Massei 2014; Bruzzone et al. 2020).

6.9.2 Persistent Underwater Sensor Grids

Given that seawater rapidly attenuates both optical and acoustic signals, no single mobile platform can deliver uninterrupted observability across a wide subsea area. Persistent underwater sensor grids, therefore, play an essential role in supplementing AUV and submarine operations. In the simulation, these grids consist of distributed nodes equipped with complementary sensing modalities, ranging from passive acoustic hydrophones and magnetometers to turbidity, dissolved-oxygen, temperature, salinity, and deformation probes. Their configuration follows the design principles used in modern ocean observatories and seismic monitoring networks, which rely on continuous baseline measurements to detect subtle environmental or structural changes.

The IA system performs data fusion across these distributed nodes, incorporating inputs from fixed sensors, mobile platforms, environmental forecasts, and oceanographic models. By reconciling heterogeneous datasets, the framework reduces uncertainty and supports more reliable anomaly detection. This approach reflects contemporary research on multi-sensor SLAM, underwater navigation, and data-fusion algorithms (Kinsey, Eustice and Whitcomb 2006; Jaffe 2015). The integrated sensor-grid model also contributes directly to resilience assessment: the system evaluates detection latency, progressive anomaly development, variable monitoring coverage, and the implications of environmental noise on observability. These aspects parallel the strategic-engineering methodologies used to model complex maritime systems and interdependent infrastructure (Bruzzone, Longo and Massei 2014).

6.9.3 Scenario Analysis

The subsea scenarios represented in the provided visual materials illustrate a highly diverse operational environment, combining AUV operations around pipelines, diver activities near submerged installations, and research submarines interacting with sensor-rich fields. In the simulation, these activities prompt coordinated responses across the IA system, which must account for the differing motion models of submarines, AUVs, and human divers. The IA manages acoustic communication limits at depth, variable endurance across platforms, and the need to deconflict navigational pathways while scheduling inspection, sampling, or maintenance tasks. These challenges are consistent with operational constraints documented in complex underwater robotics missions (Antonelli 2013; Ridao et al. 2018).

Deepwater conditions introduce additional constraints, including hydrostatic pressure, intermittent communication blackouts, challenging seafloor topography, and low optical visibility caused by suspended sediments or thermoclines. These

environmental factors directly influence navigation accuracy, mission planning, and sensor performance. As a result, redundancy and robust scheduling strategies become essential for ensuring operational continuity and reliability.

The simulation also evaluates intervention strategies, including optimal sequencing of AUV and diver deployment, adaptive routing for pipeline and cable inspections, coordinated asset positioning to minimise energy consumption, and environmental-impact assessments for various operational scenarios. The resulting insights support resilience-engineering objectives across offshore-energy operations, ecological monitoring, and research-based deep-ocean missions.

By incorporating research submarines, underwater logistics platforms, and distributed sensor grids, the simulation framework attains full-depth operational coverage and reflects the technical demands of real deep-ocean monitoring. These subsurface components significantly expand the system's capacity for scenario analysis, enabling rigorous assessments of feasibility, resilience, and long-term sustainability across a range of civilian maritime applications. The modelling approach follows established principles in underwater robotics, ocean observatory design, and strategic engineering for maritime systems, ensuring alignment with the scientific contributions of Bruzzone, Massei, Gotelli, Sinelschikov, Gadupuri, Giovannetti, Ferrari, and related research groups.

6.9.4 Modelling Disruptive and Hazardous Agents in the Multi-Domain Offshore Environment (Hostile Treats)

Ensuring the operational continuity and resilience of offshore energy installations, subsea communication cables, and distributed marine infrastructures requires the ability to simulate and analyse the full spectrum of disruptive factors that may degrade performance. In the context of maritime strategic engineering, these factors are understood as disruptive agents a term used to characterise environmental, operational, accidental, or cyber-physical phenomena that affect system behaviour without invoking any military interpretation (Bruzzone, Longo and Massei 2014). Within this framework, the simulator implements a multi-vector disturbance model that allows researchers to examine how offshore platforms, underwater inspection fields, and heterogeneous autonomous fleets respond to simultaneous pressures emerging from the aerial, surface, subsurface, and digital domains. The purpose is strictly to stress-test resilience, examine system-environment interactions, and support human-AI collaborative decision-making under challenging operational conditions (Bruzzone et al. 2020).

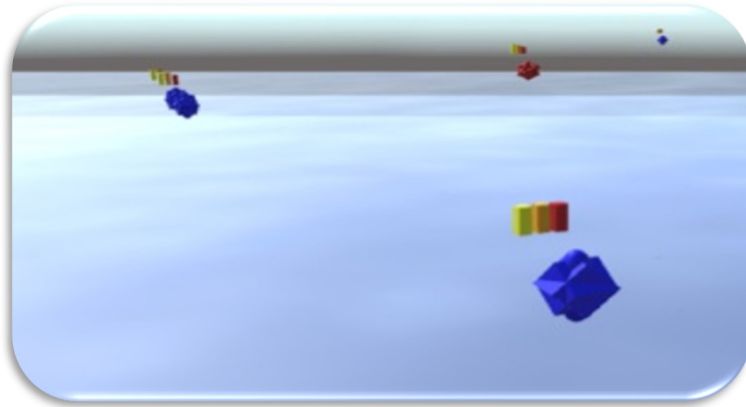


Figure 6.14: Cyber counter part of an entity (Illustrating availability, confidentiality and integrity)

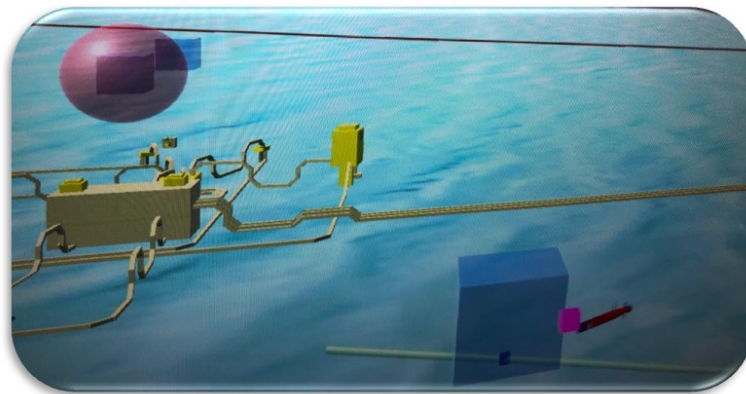


Figure 6.15: Illustration of damage of extract field

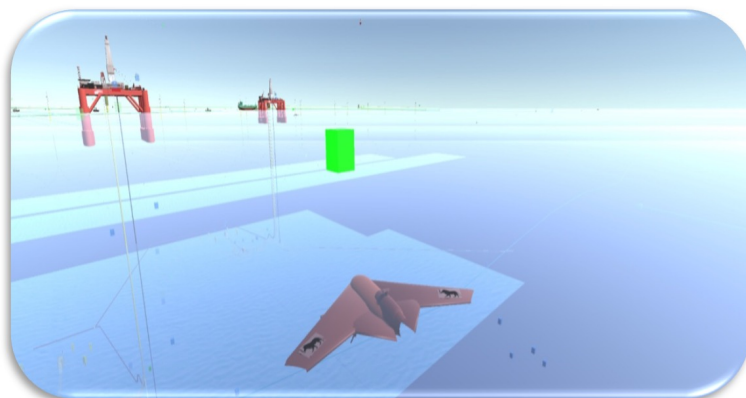


Figure 6.16: Unknown Flying Object near the extraction field

6.9.5 Characterising Multi-Vector Disruptive Agents

The simulator models four principal categories of non-military disruptive agents. These are grounded in incident types documented in offshore energy operations, underwater robotics research, and cyber-physical systems analysis.

Aerial Disturbance Agents (UAVs and Environmental Drones)

Low-flying drones and small unmanned aircraft are becoming more common around coastal infrastructure, often for commercial or recreational use. While usually harmless, they can disrupt helicopter operations, make inspections harder, or accidentally capture images of industrial sites. They might also cause electromagnetic interference with offshore platform communications. In the simulation, these aerial agents are modeled with dynamic behaviors and sensor data so the Intelligent Agent (IA) system can assess their impact. This approach matches current research in offshore-XR and inspection (Carbonell-Ruiz et al. 2021; Bruzzone, Longo and Massei 2023).

Surface-Level Disruptive Agents (Commercial Vessels and Support Craft)

Surface vessels are a common cause of accidental damage to subsea cables and pipelines. Studies show that anchor drags, drifting from propulsion failures, and navigation errors can lead to unintended contact with seafloor infrastructure (Gao and Moan 2020; Hughes Clarke 2018). The simulator models commercial ships, trawlers, survey vessels, and crew transfer boats with realistic movement and environmental factors. Some scenarios include navigation issues like poor GNSS signals to reflect real-world problems. These surface agents interact with inspection routes, OSV logistics, and AUV/ROV tasks, so the IA must keep safe distances and adjust mission plans.

Subsurface Disturbance Agents (Uncrewed Vehicles, Divers, Environmental Actors)

The underwater environment brings unique operational challenges, as shown in underwater robotics, archaeology, and engineering studies (Antonelli 2013; Paull et al. 2018; Ridao et al. 2018). These include unregistered autonomous vehicles near seabed assets, divers doing maintenance or research, and third-party objects like fishing gear or sensors entering the area by accident. Environmental factors like turbidity and sediment movement also cause disturbances. The simulation uses hydrodynamic models that match real AUV and diver behavior, so the IA can spot unexpected events and understand their impact on inspections.

Cyber-Physical Disturbances Affecting Operational Continuity As offshore systems become more digital, cyber-physical problems have a bigger impact on reliability. Issues like failed communication links, packet loss, telemetry



Figure 6.17: Divers

delays, and mismatches between digital models and real conditions can affect operations and decisions (Jones, Snider and Njuguna 2020; Tao and Qi 2019). The simulator treats these as realistic system problems, not cyberattacks, to reflect common issues like sensor drift, wrong device settings, poor network performance, or environmental interference. By tracking how these digital problems affect physical operations, the IA system can stay aware even with incomplete or unclear information.

6.9.6 Visual Confirmation of Multi-Domain Interactions

The visual materials show that offshore hazards rarely happen alone. Instead, problems often occur in several areas at once. For example, a commercial vessel might drift near a cable while the digital twin notices more packet delays on subsea telemetry. In another case, a passing vessel could stir up turbidity that affects AUV cameras just as a recreational drone enters the airspace. The simulator links visual, environmental, and communication data so the IA system can tell normal changes from real risks. This matches the multi-layer awareness methods used in advanced maritime simulation research (Bruzzone, Longo and Massei 2014; Gottelli, Bruzzone and Massei 2019).

6.9.7 Coordinated Resilience

The main reason for including multi-vector disturbance agents is to test how well the offshore system can respond to different challenges. Keeping energy production, subsea communication, and inspections running smoothly needs a strategy that combines sensor data, IA analysis, and flexible use of response resources. Resilience starts with reliable detection in every area. Sensor data

from different domains must be considered together, so an unexpected vessel path can be linked to GNSS problems instead of a deliberate move. After detection, the IA system combines information from air, surface, underwater, and cyber-physical sources to build a clear risk profile, following data-driven methods from monitoring research (Fan and Luo 2021).

After interpreting the data, resources are assigned. Autonomous vehicles like AUVs, drones, and USVs, along with crewed vessels, are sent out in ways that do not interrupt ongoing work and can quickly handle problems. In the end, resilience is measured by how well the system keeps energy production, subsea cable integrity, and inspections going despite disruptions (Bruzzone et al. 2020). By combining detection, interpretation, and response, the simulator gives a solid, science-based view of how offshore systems handle different types of disruptions. This makes it a reliable and academically strong tool for studying resilience.

6.9.8 Persistent Protection and UxV Collaboration

Offshore industrial environments are getting more complex, which shows the need for new, resilient autonomous support systems that can provide constant coverage, monitoring, and maintenance over large, changing marine areas. Traditional crewed vessels, even when advanced, face limits from logistics, crew fatigue, fuel use, and weather delays (Rudnick et al. 2018). As offshore infrastructure grows in size and importance, like with subsea grids, floating platforms, and renewable energy sites, the limits of crewed operations are becoming clearer.

The Mothership Concept is a new model in the simulation. Instead of sending out AUVs and USVs as separate units, the system uses a specially designed uncrewed surface vessel (USV) as a central, multi-purpose hub. This approach matches a wider trend in maritime robotics, where teamwork, autonomy, and cooperation between agents are key for long-term success (Antonelli 2014; Ridao et al. 2018).

This approach fits with modern engineering strategies for protecting maritime infrastructure, which focus on constant monitoring, efficient maintenance, and proactive problem detection instead of responding to threats (Bruzzone, Longo and Massei 2014). By combining different uncrewed vehicles into one system, the simulation introduces a new way to provide ongoing, crew-free protection and inspection.

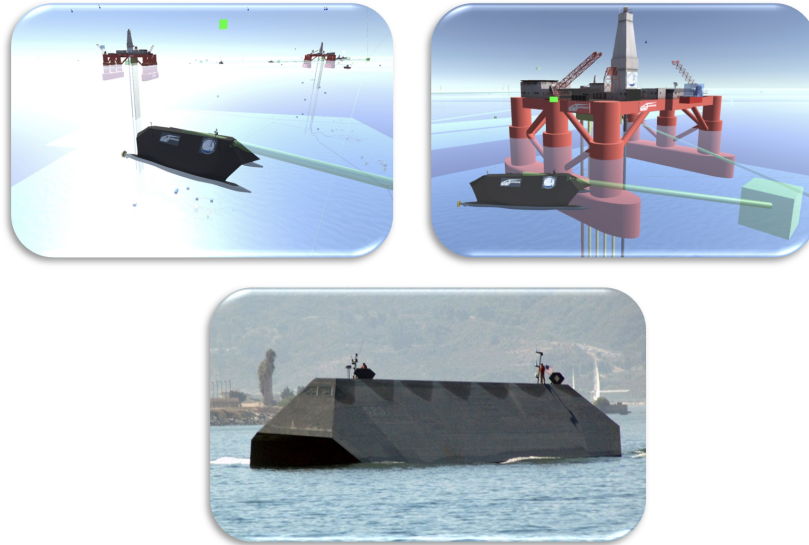


Figure 6.18: SWATH inspired USV Mothership

6.9.9 The Novelty of the SWATH-Based USV Platform

A foundational element of the Mothership architecture is the adoption of a **Small Waterplane Area Twin Hull (SWATH)** USV as the primary surface platform. The SWATH configuration is widely recognized in maritime engineering for its superior hydrodynamic behavior, offering exceptional stability, especially in high-sea-state conditions (Gao and Moan 2020). In applications involving AUV deployment and recovery, stability is a critical operational factor, as ocean waves introduce complex relative motion between the surface platform and the submerged vehicle (Kinsey, Whitcomb and Yoerger 2006).

The simulation integrates this engineering insight by modelling the SWATH platform as an **ultra-stable, long-endurance USV**, optimised for continuous offshore presence. This configuration enables the research framework to explore several capabilities essential to persistent monitoring.

Reduced Motion Response: By minimising waterplane area, the SWATH USV displays significantly lower heave, pitch, and roll compared to monohull vessels. This stability is critical for safe AUV launch and recovery (L&R) operations, typically one of the most failure-prone steps in real-world missions (Paull et al. 2018).

6.10 The Collaborative Autonomous System Module

Extended Endurance and Crew-Free Operation: The USV is modeled as a fully autonomous craft capable of remaining on-station for extended periods, potentially weeks, thanks to low crew requirements and optimised energy usage. This capability supports the broader need for persistent protection without the logistical burden of manned platforms.

Reduced Operational Risk: As an uncrewed asset, the SWATH USV eliminates human exposure to harsh maritime conditions, aligning with modern safety and risk-reduction principles in offshore operations (Gotelli, Bruzzone and Massei 2019). By incorporating this platform, the simulation advances a realistic, high-fidelity representation of next-generation offshore inspection and protection strategies, using well-founded hydrodynamic and autonomous-systems theory.

6.10 The Collaborative Autonomous System Module

The main innovation in the Mothership simulation is not just the SWATH USV itself, but the way it supports a group of autonomous subsystems working together. The USV acts as a central hub for logistics, communication, and operations, managing a rotating fleet of AUVs. This setup greatly increases the system's ability to carry out ongoing subsea inspections.

fig. 6.19 This approach lets different AUVs focus on specific tasks, such as imaging, acoustic mapping, or leak detection. It also reduces downtime because one AUV can start its mission as soon as another returns for service or to upload data.

Integrated AUV Payload System Within the simulation, the USV hosts a rotational revolver system carrying three AUVs, each capable of performing inspection, mapping, or environmental sensing tasks. This architectural choice reflects established trends in AUV operations, where multi-vehicle coordination significantly expands spatial coverage and operational robustness (Ridao et al. 2018; Rudnick et al. 2018). The revolver design supports the sequential deployment of AUVs to maintain uninterrupted surveillance cycles, Rapid role reassignment, allowing different AUVs to specialize in unique tasks (e.g., imaging, acoustic mapping, leak detection). Reduced downtime, as one AUV can depart immediately when another returns for service or data upload.

The Catcher System and the Challenge of AUV Recovery One of the most complex subsystems in the model is the catcher mechanism, which is built for autonomous AUV retrieval. In practice, recovering AUVs is a major challenge

6.10 The Collaborative Autonomous System Module

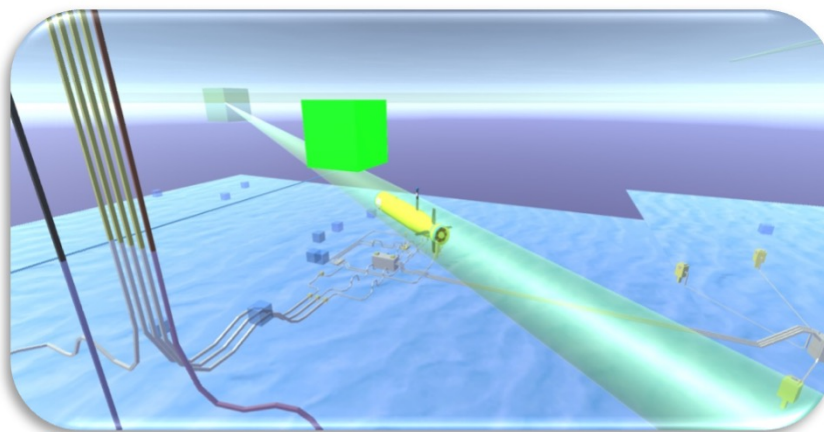


Figure 6.19: AUV deployment for inspection

because of unpredictable environments, noise from waves, and the difficulty of moving submerged vehicles near the surface (Kinsey, Whitcomb and Yoerger 2006).

In the simulation, the catcher is a precise docking system that captures AUVs as they approach the USV. It helps prevent drift from water currents, secures the AUV under the USV for safe transport or charging, and sends mission data to the cyber layer for analysis.

This modeling is consistent with contemporary research on advanced docking, subsea homing, and acoustic navigation challenges (Paull et al. 2018).

AI-Driven Coordination and Decision-Making The USV, its AUV fleet, and the main command system work together through real-time decisions made by Intelligent Agents. These agents choose the best launch times based on sea conditions, battery levels, and the environment. They also manage the movement of multiple underwater vehicles to avoid conflicts and can quickly change tasks based on inspection needs or maintenance.

Such coordination reflects the multi-agent autonomy concepts described in underwater robotics literature (Antonelli 2014; Ridao et al. 2018).

6.10.1 Interoperability and Strategic Resilience

Combining the USV and AUVs directly supports the main goals of this thesis: making systems work together, ensuring ongoing protection, and improving offshore infrastructure resilience. **Seamless Communication and Multi-Domain Data Exchange** The USV serves as the main communication

6.10 The Collaborative Autonomous System Module

hub. It connects low-bandwidth acoustic signals from underwater AUVs with high-bandwidth radio or satellite links to the Command and Control (C2) cyber layer and the real-time tools used by human operators. This multi-domain integration is consistent with research emphasizing reliable underwater–surface–air networking architectures (Paull et al. 2018; Jones et al. 2020).

Proactive Readiness and Maintenance Efficiency

Because the USV is always present, the system can quickly launch an AUV to inspect pipelines, subsea trees, cables, renewable energy foundations, or environmental issues. Rotating vehicles helps reduce blind spots during inspections. This cuts downtime and prevents small problems from becoming bigger issues.

Resilience Through Redundancy and Multi-Agent Coordination

Having several AUVs on one USV adds redundancy. If one AUV fails, another can take its place immediately. The system also supports distributed sensing, triangulation, and running missions in parallel.

This directly reflects resilience engineering concepts in critical-infrastructure modeling (Bruzzone et al. 2020; Massei and Bruzzone 2010). The simulation framework provides an integrated and practical model for ongoing offshore protection. Using the Mothership Concept, it takes a scientific approach to long-term maritime autonomy, models how surface and underwater vehicles work together, and offers practical solutions to engineering challenges like launch, recovery, endurance, and communication. It also connects closely to current research in offshore robotics, digitalization, and infrastructure resilience.

By building on proven maritime research, this section supports the main goal of creating a strong, realistic, and ethical framework for protecting marine infrastructure.

6.10.2 Comprehensive Scenario Replication

The engineering framework in this research relies on accurately modeling the Extended Maritime Framework (EMF). The EMF sees the modern maritime environment as a set of closely connected layers: sea surface, underwater, coastal, air, space, and cyberspace, where operations, risks, and decisions happen across all domains (Bruzzone et al. 2020). By using this multi-layered approach, the research goes beyond traditional single-domain models and captures the complex, interconnected nature of marine operations.

A key challenge discussed here is showing how different domains interact with each other. For example, launching a UAV in the air can quickly affect communication bandwidth in cyberspace or disrupt underwater acoustic sensing

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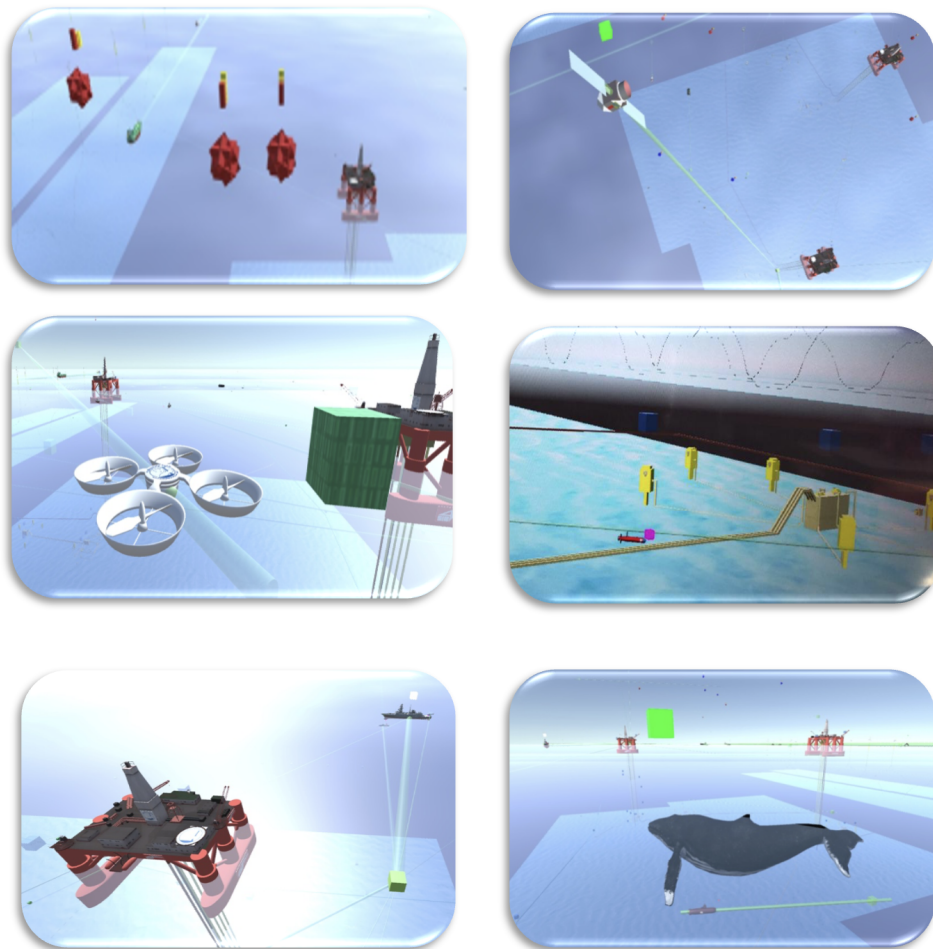


Figure 6.20: Six dimensional operational space (Cyber space, Space, Air, Seabed, Water Surface, Underwater)

6.10 The Collaborative Autonomous System Module

(Lurton 2010; Jaffe 2015). The simulation treats the maritime environment as a connected system where effects often cross between domains. This approach is important for testing resilience, since problems rarely stay in just one area.

6.10.3 The Six-Dimensional Operational Space

Including all six EMF dimensions in the simulation is based on research showing that offshore infrastructure depends on processes across spatial, biological, environmental, and cyber-physical domains (Gao and Moan 2020; Paull et al. 2018). Each area has its own limits and challenges, so modeling them together is important.

Space and Cyberspace Layer Integration

The space and cyberspace layers together provide the main information and communication support for modern offshore operations. Satellite services such as navigation, Earth observation, and communication are essential for positioning, remote monitoring, and long-distance coordination (Tao and Qi 2019). These services can be disrupted by environmental events like space weather or by technical problems such as crowded radio frequencies. Below satellites, cyberspace includes control networks and digital twin data flows (Jones et al. 2020). Research shows these systems can face issues like delays, lost data, or corruption, which can cause problems for the whole platform.

Surface Domain Representation The air and surface domains are the main areas for operations, logistics, and safety monitoring (Carbonell-Ruiz et al. 2021). The air domain covers commercial planes, search-and-rescue helicopters, and special UAVs for inspection and sensing. The simulation models these with realistic paths, environmental limits, and sensor features.

Similarly, the surface domain contains commercial shipping lanes, fishing vessels, and support craft, each contributing to the environmental “background noise” that complicates sensing and traffic management. Studies on maritime traffic monitoring emphasize that these benign actors generate sensor clutter that can obscure both anomalies and early-warning signals (Hughes Clarke 2018).

Underwater and Coastal Domain Complexity The underwater and coastal layers have the most structural and ecological variety. Subsea pipelines, cables, sensors, and underwater vehicles work in waters with strong currents, layers, murkiness, and uneven conditions (Lurton 2010; Blondel 2010). The simulation includes seabed shape, depth, marine life movement, and sediment spread, all of which affect sound travel and monitoring accuracy underwater (Chiang and Chen 2012).

The coastal zone connects offshore operations with land-based command centers,

6.10 The Collaborative Autonomous System Module

logistics hubs, and key digital infrastructure. By modeling these links, the simulation shows the full process from coastal planning to underwater work.

6.10.4 The Role of Modeled Noise and External Factors

One of the hallmarks of high-fidelity marine simulation is the explicit treatment of external variables that are rarely central to threat analysis but significantly influence operational performance. Researchers in underwater robotics and ocean observation consistently highlight the disruptive impact of unstructured environmental variables such as marine fauna, recreational traffic, and floating debris on sensing, navigation, and communication (Jaffe 2015; Rudnick et al. 2018). Consistent with this literature, the simulation integrates a full set of these external factors as part of its baseline operational scenario.

Background Traffic and Interference Commercial and recreational traffic introduces dynamic clutter into sensor-rich environments. Automatic Identification System (AIS) signals, radar reflections, and electromagnetic emissions require continuous filtering to avoid misclassification of benign movements as anomalies (Wackrow and Chandler 2011). By incorporating these elements, the simulation tests the robustness of both human operators and intelligent agents in distinguishing between routine operations and potential risks.

Marine Life Modeling Marine mammals and large fish schools are modeled due to their influence on sonar backscatter and acoustic signatures (Lurton 2010). Their movement can degrade subsea sensing accuracy or be mistaken for autonomous underwater vehicles (AUVs), especially in low-visibility environments. This dual impact conservation consideration and sensing interference aligns with modern ecological best practices for ocean robotics deployment (Ridao et al. 2018).

Non-Hostile Physical Objects Fixed buoys, abandoned fishing gear, and drifting debris add to environmental complexity. The simulation includes them to test the system's ability to interpret unclear readings, prevent interference, and avoid unnecessary operational disruptions.

6.10.5 Enhancing Operational Readiness and Cognitive Resilience

The modeling choices described above serve an overarching objective: enhancing the cognitive resilience, situational awareness, and decision-making support available to human operators. Cognitive resilience defined as the ability to maintain clarity and prioritization under ambiguous or conflicting information

6.10 The Collaborative Autonomous System Module

has been identified in the literature as a critical determinant of safe offshore operations (Domingo et al. 2022). By exposing operators to realistic levels of noise, uncertainty, and distraction, the simulation environment trains them to manage complexity effectively.

Noise Mitigation Validation The test scenarios check if the intelligent agent framework can do advanced filtering, pattern recognition, and contextual inference to reduce noise while keeping important information. This skill is essential for real-world uses involving multi-sensor fusion, where too much data can hide subtle but important anomalies (Fan and Luo 2021).

Allocation Under Ambiguity fig. 6.21, The most challenging aspect of offshore decision-making is the necessity to act under uncertainty. The simulation obliges human decision-makers to make choices based on incomplete or conflicting information reflecting operational realities such as poor weather, communications latency, or interference. By embedding ambiguity into the training environment, the simulation reinforces resilience principles while enabling more informed long-term strategy development (Bruzzone, Longo and Mass 2023).

6.10.6 Cybersecurity and Communications

Offshore industrial systems depend on a network that links subsea equipment, autonomous vehicles, support ships, and coastal control centers. As marine operations use more digital tools, tasks such as inspections, environmental monitoring, and equipment checks all require stable communication across different channels. Research shows that communication networks are now essential for keeping maritime systems resilient. In the simulation, communication links are modeled as changing, state-dependent connections. If one fails or weakens, it can affect the entire system.

Fig: Cyber-Physical Communication Infrastructure

This approach shows that offshore systems face risks from both physical and cyber disruptions. Issues with data, sensors, or keeping digital twins in sync can all impact operations. The simulation treats cybersecurity as a core part of the system, using methods from other marine and industrial simulations. Rather than separating digital and physical parts, the model includes communication needs in how each device and agent works. This helps show how communication problems can affect decisions and safety.

6.10 The Collaborative Autonomous System Module

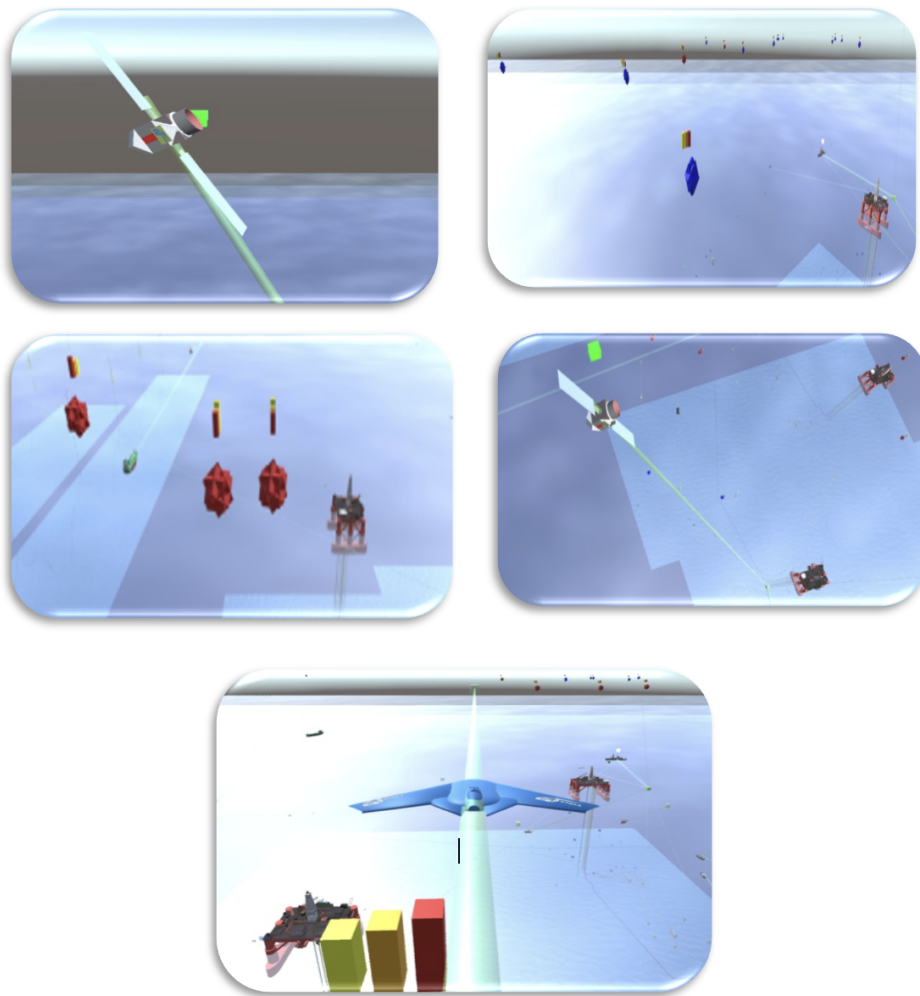


Figure 6.21: Cyber-Physical Communication Infrastructure

6.10.7 The Heterogeneous Network Architecture

The simulation uses three main types of communication: subsea acoustic channels, short-range radio or line-of-sight links, and satellite connections. Each type is modeled with real-world data from marine communication studies, so the simulation matches the limits found in actual offshore work. Underwater, acoustic communication is the main method, but it has low bandwidth, high delay, and is affected by water layers and murky conditions. These limits control how often AUVs can send data and how quickly seabed sensors update. Radio and microwave links on the surface connect UAVs, USVs, and shore stations. These links are faster and have less delay, but they need a clear line of sight and can be affected by weather. This is important for planning inspection routes and how quickly control centers can respond. Satellite links cover large areas but have more delay, so they are mainly used for updates, long-distance syncing, or as a backup. The simulation uses a layered approach to model these channels, making sure the digital twin and agent systems face the same limits as real equipment. and Integrity Modeling

6.10.8 The Cyber Correspondent and Integrity Modeling

Each simulated vessel, AUV, UAV, sensor, or asset has a digital counterpart that manages its communication, checks data, and keeps it in sync with the rest of the system. This follows cyber-physical modeling, where every physical item has a digital version to help with decisions and coordination. The digital counterpart tracks if communication is working, so the model can show what happens when channels are weak, radio signals drop, or satellite links are slow.

The digitThe digital component also checks data quality. It looks for sensor errors, environmental problems, or bad data by comparing different sources and finding mismatches between what is measured and what is expected. This is similar to how real systems monitor equipment health and check digital twins. The model also keeps sensitive data private, which is important for industrial operations, even though the simulation is not military.

6.10.9 Dynamic Cyber Resilience

The simulation tests cyber resilience during real operations, not just in a perfect or fixed network. It checks how communication problems affect inspections, ship movements, changing conditions, and how autonomous agents act. If an AUV loses its acoustic link because of stirred-up sediment or marine life, the system

6.11 Heterogeneous Network Architecture in the Offshore Domain

can switch to a USV relay or let the AUV work on its own until the link returns. This flexible response matches real-world strategies used in ocean research and robotics.

When bandwidth is limited, the system sends only the most important data, like structural health, environmental warnings, and navigation details. Less urgent information is delayed. This follows fault-tolerant design ideas from other industrial simulations. The digital counterpart also looks for problems by comparing real data with what is expected. If it finds odd signals, wrong depths, or strange movements, it sends an alert so the team can check or move inspection resources. This is similar to how digital twins spot issues in real marine systems.

6.10.10 Cyber & Communications over Heterogeneous Networks

Modern offshore systems rely on steady, reliable communication to connect ships, UAVs, AUVs, seabed sensors, and shore centers. Communication is not just a support service; it is the main link for digital control, coordinating autonomous inspections, and tracking what is happening in the system. New research in cyber-physical systems shows that keeping these mixed networks stable is key for running complex marine operations, especially when monitoring energy systems, subsea cables, or offshore platforms.

In this simulation, communication is modeled as a changing system with underwater acoustic, radio, and satellite links, all working under real-world limits. This layered setup is based on earlier marine and port modeling work, where having networks that work together is seen as crucial for good simulation and system resilience.

6.11 Heterogeneous Network Architecture in the Offshore Domain

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6.11.1 The Cyber Correspondent Model

Each physical entity in the simulation is matched with a cyber correspondent to connect communication, environmental, operational, and autonomous-agent processes. This digital counterpart manages communication links, checks data integrity, and keeps the entity's state updated in the digital system. The idea comes from digital-twin engineering and distributed simulation, which combine physical actions, sensor data, and communication logic to keep the system consistent (Qi and Tao 2019; Bruzzone et al. 2011).

The cyber correspondent handles three key aspects of cyber-physical consistency. First, availability means keeping communication open even when bandwidth is limited, packets are lost, or there is acoustic interference. This is especially important for subsea nodes, where the environment often disrupts signals. Second, integrity involves checking that exchanged information stays unchanged, and flagging issues like odd navigation reports or data errors from noise or equipment problems. This is similar to how underwater navigation systems check for errors caused by drift, sensor bias, or poor telemetry (Jaffe 2015; Kinsey et al. 2006). Third, confidentiality protects sensitive industrial data, planning details, and maintenance records from unauthorized access, even in civil maritime settings. In the simulation, this is managed through authentication and secure channels.

Together, these mechanisms establish a strong coupling between digital and physical layers, enabling the system to evaluate how communication failures or inconsistencies propagate into operational performance. This digital parallelism

6.11 Heterogeneous Network Architecture in the Offshore Domain

is fully aligned with distributed simulation methodologies that treat cyber dependencies as first-class components of maritime operational modelling (Bruzzone, Longo and Massei 2014).

6.11.2 Cyber Resilience Under Dynamic Operational Conditions

The main goal of the simulation is to test how well the system can handle cyber problems in real offshore conditions that keep changing. Instead of seeing communication failures as one-off issues, the system puts them into real-world situations where weather, vessel movement, and digital errors all mix together. This way, resilience comes from the system adapting and coordinating across different layers, not just from making each part stronger on its own.

The simulation looks at how autonomous inspection units adjust when communication becomes unreliable. For example, if an AUV loses its acoustic link because of murky water or equipment noise, the system may switch to a low-communication mode and use dead-reckoning or send messages through a nearby USV with better RF links. These actions are based on real AUV mission management seen in marine robotics research (Paull et al. 2018; Rudnick et al. 2018).

When bandwidth is tight, the system sends only the most important data, like pressure or navigation info, and skips less critical sensor readings. This kind of smart prioritization helps keep things running smoothly, as seen in industrial system models.

The cyber correspondent also helps spot mismatches between what is happening physically and what the digital data shows. For instance, if a ship's AIS says it is not moving but radar shows it is speeding up, the system finds this issue and updates risk assessments. The same checks are used underwater to tell if sensor data is faulty or if there are real changes in pressure or structure. These checks are similar to those used in digital-twin systems for managing maritime infrastructure and assets (Jones et al. 2020).

All these mechanisms build a cyber-physical environment that supports thorough resilience analysis. Instead of assuming communication always works, the simulation treats it as something that can change with the environment, operations, and system factors. This makes it a reliable tool for studying decision-making, asset coordination, and safety in different marine networks.

Chapter 7

VERIFICATION AND VALIDATION OF THE SIMULATION FRAMEWORK

The nature of the research project requires verification of the model's correctness in order to determine its suitability for the intended purpose and to identify the limits of its applicability. The primary objective is therefore to evaluate whether the proposed modelling approach is appropriate for the problem under investigation. In the present study, the analysis focuses on the capability of the simulated system to detect threats to offshore infrastructure. Consequently, it is necessary to verify that the implemented unit dynamics and system properties produce behaviour that is both physically realistic and numerically stable.

To address this requirement, a two-phase validation methodology is adopted. The first phase aims to determine the number of simulation replications required to obtain statistically reliable results. This is achieved by analysing the Mean Squared pure Error (MSpE) in order to evaluate the convergence of simulation outputs. The second phase consists of conducting a 2k factorial experiment to assess the sensitivity of the system to variations in selected initial and boundary conditions. This approach enables the identification of the most influential factors affecting system behaviour and supports the assessment of model robustness under different operating scenarios.

7.0.1 MSpE and Convergence Analysis

Before evaluating the physical realism of the model, it is necessary to confirm that the simulation outputs are not dominated by stochastic variability. The

simulation framework includes several probabilistic mechanisms, such as target generation, engagement variability, and tracking transitions. For this reason, a convergence analysis is required to ensure that the observed results reflect stable system behaviour rather than random fluctuations. To address this requirement, the Mean Squared pure Error (M_{SpE}) method is used as the primary tool for assessing convergence.

Extended exploratory simulations were first conducted to observe the temporal evolution of damage inflicted on the protected infrastructure. These preliminary runs indicated that the vast majority of measurable damage occurred within the first two days of simulated time (172800 seconds). Beyond this point, the rate of additional damage became negligible and the system behavior stabilized. Based on this observation, the duration of the experimental runs was limited to a maximum simulation time of 200000 seconds. This upper bound ensures that the entire critical engagement period is captured while avoiding unnecessary computational overhead. The cumulative damage inflicted on the infrastructure was therefore evaluated at the end of this fixed simulation interval.

The analysis begins with the definition of a stochastic baseline configuration. The simulation is executed multiple times, while keeping all input parameters fixed at their central values. These central values correspond to the average expected values located approximately in the middle of the anticipated operational range of each parameter. This configuration therefore represents a neutral reference scenario against which the results of later experimental variations can be compared.

During these repeated simulations, selected output metrics, such as accumulated damage or tracking duration, are monitored over time. The variability of these outputs across independent runs is then examined in order to determine whether the results remain influenced by stochastic effects.

Scenario	(i_1) (Range)	(i_2) (Own Speed)	(i_3) (Enemy Speed)	Expected Fidelity Behavior
1	Min	Min	Min	Late detection; low damage
2	Min	Min	Max	Late detection; unstable tracking
3	Min	Max	Min	Moderate detection; interception advantage
4	Min	Max	Max	High-speed intercept
5	Max	Min	Min	Early detection; stable tracking
6	Max	Min	Max	Early detection; track degradation possible
7	Max	Max	Min	High persistence; strong engagement
8	Max	Max	Max	Maximum dynamic stress; highest system load

Figure 7.1: Enemy Expected Fidelity Behavior

7.1 Analysis and Results

In this study, the stabilization of variance is assessed graphically. The variance of the observed metrics across simulation replications is plotted as function of number of replications, and convergence is considered to be achieved when the variance curve approaches a stable plateau and no longer exhibits fluctuations. Once this stabilization is observed, the baseline configuration is adopted as the reference scenario representing nominal system behaviour and is subsequently used as the comparison point for the factorial experimentation phase. Hence, identified number of replications is used for all following experimentation.

During experimentation following results were obtained for First detection time variance

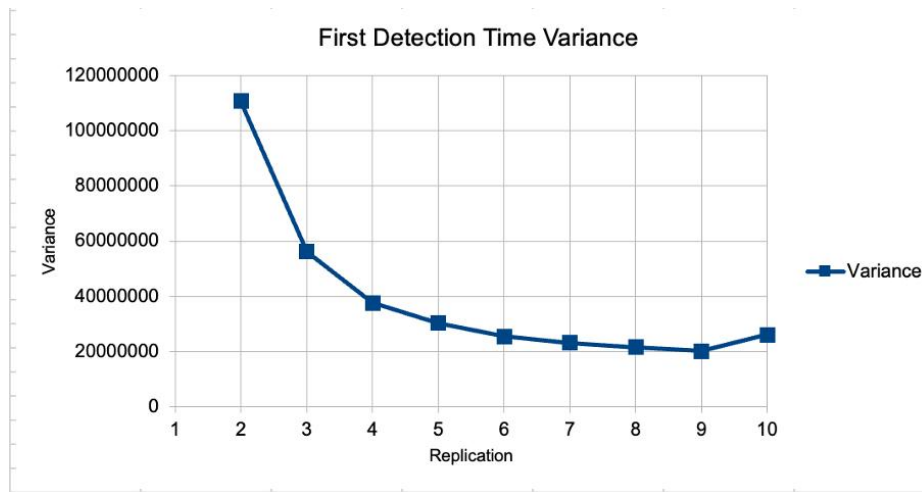


Figure 7.2: First detection time variance

7.1.1 Total damage of Infrastructure Variance:

From the chart it is possible to observe that the variance stabilizes at approximately 4th replication.

Implementation-level validation focuses on confirming that the simulation correctly represents the intended analytical definitions and that data collection within the model is performed in a consistent and reliable manner.

The simulation regulates the frequency of logged data using a conditional threshold applied to an internal update counter. Logging occurs only after the counter exceeds a predefined value, which effectively throttles the sampling rate. This mechanism ensures that output data are collected at consistent time intervals and prevents excessive logging that could introduce noise or distort statistical analysis. By controlling the logging frequency, the simulation maintains deterministic sampling intervals. This time reference allows the results of different simulation runs and experimental configurations to be aligned and compared consistently. In all cases the total duration of experimentation is limited to the same fixed value for practical reasons.

The implementation of the mission-level performance metric is directly reflected in the simulation through the accumulation of damage values associated with each hostile unit. The model records the damage sustained by individual infrastructure elements and aggregates the reduction in their integrity values over the course of the simulation. The correspondence between the analytical definition of the metric and its implementation in the simulation code ensures

7.1 Analysis and Results

Table 7.1: Total Damage of Infrastructure over 200,000 seconds

Replication	Total Damage after 200,000 s	Variance
1	2498	-
2	1900	178,802
3	2285	91,866
4	2189	61,618
5	1887	68,126
6	1898	65,236
7	1900	60,634
8	1900	56,002
9	1800	56,348
10	1800	55,311
11	2200	53,212
12	1900	49,643
13	2000	45,519
14	1900	42,915
15	1882	40,843
16	1896	38,744
17	2300	41,987
18	1800	41,919
19	1900	40,079
20	2100	38,561

that the reported results accurately reflect the intended model behaviour. This direct mapping between conceptual definition and code implementation improves transparency, facilitates reproducibility, and supports the scientific validity of the analysis.

Several manual control mechanisms are implemented in order to support targeted verification of specific model behaviours. One control allows the stochastic target generation process to be reset during runtime. This capability is used during convergence analysis to reinitialize the stochastic state of the simulation when required. Additional controls allow the positional states of entities within the environment to be forced into predefined configurations. These configurations are used to verify the correctness of geometric relationships within the detection model, particularly those related to sensor range and spatial intersection behaviour.

Such mechanisms allow to reproduce boundary conditions in a controlled and deterministic manner, enabling direct inspection of the simulation response under specific geometric or stochastic scenarios.

7.2 (2k) Factorial Experiment

After statistical stability of the simulation outputs is established, the next step is to examine model fidelity under controlled variations of key parameters. For this purpose, a factorial experimental design is applied. This approach enables systematic exploration of the effects of multiple input variables and their interactions by evaluating system behaviour at the extreme bounds of their expected operating ranges.

In this study, three input factors are considered. A full factorial design with three factors therefore results in eight experimental configurations. Each configuration represents a unique combination of the minimum and maximum values of the selected variables. This structured testing procedure allows the behaviour of the simulation framework to be examined under conditions that extend beyond nominal operating levels, thereby verifying that the implemented models remain logically consistent and numerically stable when subjected to significant parameter variation.

The first factor is the detector range. Two levels are considered: a reduced value corresponding to 70% of the nominal range (inefficient sensors or unfavorable environmental conditions) and an expanded value corresponding to one 150% of the nominal range (improved sensors). Reducing the range represents degraded situational awareness, while increasing the range simulates a larger detection range. This parameter variation tests the geometric consistency of the detection model, particularly the interaction between sensor coverage and target trajectories. The second factor is the maximum speed of the own ship. The tested values correspond to 70% and 120% percent of the nominal speed. Lower values represent reduced patrolling speed but lower fuel consumption, while higher values increase them. This factor is used to verify the consistency of the propulsion and kinematic motion modelling implemented in the simulation. The third factor is the maximum speed of the hostile units. As with the patrol ship speed, the parameter is varied between 70% and 120% of its nominal value. Lower speeds correspond to relatively stable tracking conditions, whereas higher speeds increase the difficulty of maintaining target tracks.

Model fidelity is evaluated using three output indicators that describe different stages of the sensor–tracking–engagement process.

The first metric is the time required for the system to achieve the initial detection of a target. This value corresponds to the moment when a sensor first intersects with the target trajectory. It provides a direct test of the correctness of the sensor field-of-view geometry and the spatial intersection logic implemented in

the detection model. Under normal conditions, an increase in detector range should result in earlier detection events.

The second metric measures tracking persistence. This quantity represents the proportion of time during a fixed observation window in which the target remains successfully tracked by the system. It is used to assess the stability of the tracking process, including the behaviour of state transitions and the ability of the model to maintain track continuity when targets move at higher speeds.

The third metric represents the cumulative damage inflicted on hostile targets during the simulation. Each target is assumed to possess a normalized health value, and the total reduction in this value across all targets is used as a mission-level performance indicator. This metric reflects the overall consistency of the sensor-to-engagement chain implemented within the simulation.

The results of the factorial experiment are then organized into an eight-run comparison matrix, where each row corresponds to a specific combination of the minimum and maximum levels of the three input factors. This structure enables direct comparison of system responses across the full set of parameter combinations.

Conclusions

A full factorial experiment with three factors and four replications per treatment combination was conducted to evaluate the influence of detection capability, enemy speed, and interceptor speed on the accumulated damage measured at a fixed simulation time horizon. The analysis follows the standard factorial methodology described by Montgomery and allows the estimation of the individual and combined influence of the examined parameters.

7.3 DOE 2³ Calculator

The results show that enemy speed increases the resulting damage. When the adversary moves faster, interception becomes more difficult and the accumulated damage grows. The estimated magnitude of this effect corresponds to an increase of roughly 130 units of damage between the low and high levels of the enemy speed parameter.

Interceptor speed has the opposite influence. Higher interceptor velocity improves the ability to reach the target earlier and therefore reduces the damage accumulated during the simulation. The estimated reduction associated with

7.3 DOE 2³ Calculator

Treatment	A	B	C	AB	AC	BC	ABC	Rep 1	Rep 2	Rep 3	Rep 4	Cell Total	Cell Mean
(1)	-1	-1	-1	1	1	1	-1	2593,7	2384,7	1900,0	2300,0	9178,3180	2294,5795
a	1	-1	-1	-1	-1	1	1	1896,6	1900,0	2600,0	1900,0	8296,5920	2074,1480
b	-1	1	-1	-1	1	-1	1	2777,3	2700,0	1898,7	2600,0	9976,0700	2494,0175
ab	1	1	-1	1	-1	-1	-1	1900,0	2498,5	1890,6	2100,0	8389,1590	2097,2898
c	-1	-1	1	1	-1	-1	1	1900,0	1900,0	1789,5	1687,9	7277,4070	1819,3518
ac	1	-1	1	-1	1	-1	-1	1898,3	1900,0	1898,0	1900,0	7596,3130	1899,0783
bc	-1	1	1	-1	-1	1	-1	1900,0	1882,5	1894,5	2696,8	8373,7860	2093,4465
abc	1	1	1	1	1	1	1	1900,0	1900,0	1980,4	1900,0	7680,3720	1920,0930

Figure 7.3: DOE 2³ Calculator

increasing the interceptor speed is approximately 180 damage units.

Detection capability also strongly affects the system performance. Lower detection range leads to delayed reaction and therefore higher damage, while earlier detection improves interception conditions and reduces the total damage. The estimated magnitude of this factor is on the order of 300 damage units, indicating that detection capability is one of the dominant drivers of system performance.

Interaction effects indicate that detection capability and interceptor speed reinforce each other. When both parameters are favorable, the reduction in damage is greater than would be expected from their individual effects alone. Improved detection also reduces the sensitivity of the system to increases in enemy speed.

Indeed, the results indicate that factor C (patrol boats' speed) has the largest influence on the response, followed by factors A (detection range) and B (enemy boats' speed), while the interaction terms are substantially smaller. The sums of squares confirm this observation, showing that factor C contributes the largest portion of the response variability, whereas the two- and three-factor interactions have comparatively minor influence.

7.3.1 Effects and Contrasts

The visual result representation summarizes the estimated effects of the three studied factors and their interactions on the accumulated damage response. The contrast column represents the calculated difference between the response totals of treatment combinations according to the factorial sign structure, while the estimate column expresses the corresponding effect size for each factor.

Effects and Contrasts			
Effect	Contrast	Estimate	SS Effect
A	-2843,1	-177,7	252608,5
B	2070,8	129,4	134001,1
C	-4912,3	-307,0	754072,1
AB	-1717,5	-107,3	92182,0
AC	2094,1	130,9	137043,0
BC	290,1	18,1	2630,3
ABC	-307,1	-19,2	2947,9

Figure 7.4: Effects and Contrasts

ANOVA Summary				
Source	DF	SS	MS	F
A	1	252609	252609	3,234
B	1	134001	134001	1,716
C	1	754072	754072	9,655
AB	1	92182	92182	1,180
AC	1	137043	137043	1,755
BC	1	2630	2630	0,034
ABC	1	2948	2948	0,038
Model	7	1375485	196498	2,516
Error	24	1874404	78100	
Total	31	3249889		

Figure 7.5: ANOVA summary

The visual result representation with ANOVA Summary decomposes the total variability of the response into contributions from the main factors, their interactions, and the experimental error. The F statistics compare the variance explained by each factor with the r

The results show that factor C produces the largest contribution to the response variability and the highest F value, indicating the strongest influence on accumulated damage. Factors A and B show smaller effects, while the interaction terms have low F values and therefore contribute only marginally to the overall variability of the system response.

Following figures illustrate these findings in graphical way.

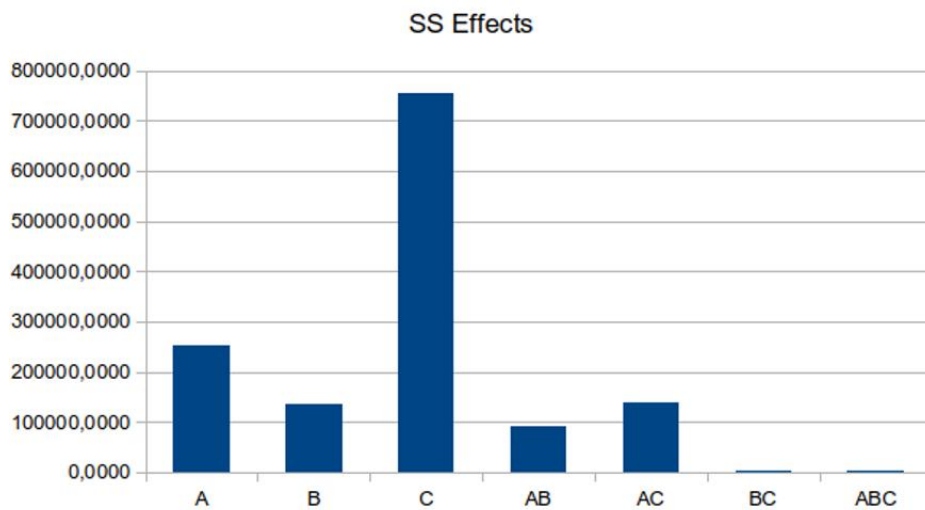


Figure 7.6: SS Effects

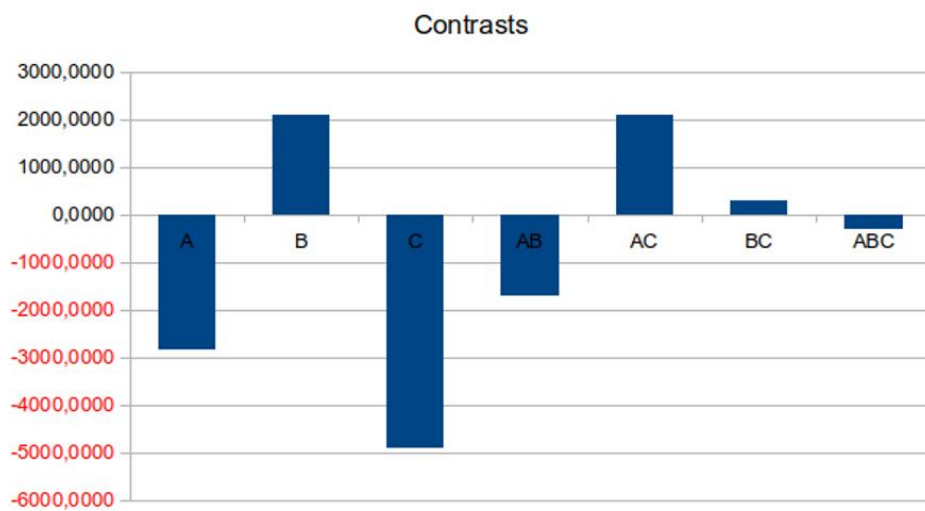


Figure 7.7: Contrasts

Overall, the results indicate that system performance is primarily controlled by detection capability and interceptor speed, both of which substantially reduce accumulated damage when improved. Enemy speed has a smaller but still noticeable influence, increasing the resulting damage as the threat becomes more difficult to intercept.

Chapter 8

AI AND MACHINE LEARNING TECHNIQUES FOR ANOMALY DETECTION AND DECISION SUPPORT

Imagine a brilliant sunrise over a vast offshore wind farm, turbines turning steadily as the waves crash. Suddenly, unforeseen vibrations ripple through the structure due to an undetected fault, leading to substantial power outages costing millions and putting thousands in the dark. This scenario highlights the critical need for robust early anomaly detection systems. Modern offshore infrastructures, such as subsea cables, renewable energy systems, ports, and sensor networks, face uncertain and complex environments with constant disturbances from air, sea, and cyber sources. Their resilience relies on early anomaly detection, risk assessment, and timely responses. In this setting, Artificial Intelligence (AI) and Machine Learning (ML) are essential for turning large, varied datasets into useful insights, improving human-machine teamwork, and making digital-twin systems more predictive. The simulator for this research creates a multi-domain environment where autonomous vehicles, environmental factors, communication networks, and offshore assets interact. It uses an HLA-based distributed simulation, resulting in large amounts of both synthetic and real data. This data includes sonar images, bathymetry, time-series, telemetry, traffic patterns, and diagnostic traces. Advanced computational methods are essential to interpret this data effectively. These methods learn from complex patterns, handle uncertainty, and adapt to changing conditions. AI and ML are integrated into the Strategic Engineering framework. They provide real-time anomaly detection and assist in making decisions for inspection, maintenance, and risk reduction.

In maritime research, modeling and simulation have often used discrete-event simulation, agent-based modeling, and distributed systems to represent ports, logistics, and industry (Massei & Bruzzone 2010; Bruzzone et al. 2011; Gotelli et al. 2019). This work builds on that by adding modern, data-driven AI to a federated simulation, allowing automated analysis of sensor data, threat classification, and improved operational responses. By combining traditional simulation with adaptive learning, the system can now interpret new situations, spot unexpected changes, and suggest context-aware actions. The offshore domain offers unique challenges and opportunities for AI-driven decision support. Marine environments are characterized by noisy sensor data, intermittent communication links, non-stationary environmental processes, and high operational costs for inspection or intervention. For example, the average cost of inspecting offshore facilities can reach up to €50,000 per day, while downtime due to undetected anomalies might cost millions of dollars annually. Autonomous underwater vehicles must navigate with uncertain acoustic ranging; surface vessels may be affected by environmental or cyber-physical disturbances; and subsea pipelines and cables often show early signs of degradation only through subtle environmental changes. Subsea cables have an approximate failure rate of 4 per 10,000 km annually, which only underscores the importance of predictive capabilities. These conditions make AI particularly valuable for identifying anomalies that would be difficult to detect through deterministic models alone. They also support predictive maintenance by estimating future degradation trajectories, operational risks, and resource-allocation strategies.

This chapter explores how supervised, unsupervised, reinforcement, and deep learning methods improve the Strategic Engineering process. Before diving into the specifics, it is essential to frame each technique with a primary "engineering job" it addresses: Supervised learning excels at anomaly classification, where operational states must be clearly distinguished. Unsupervised learning uncovers hidden patterns and anomalies, making it ideal for detecting the unexpected. Reinforcement learning is best suited for optimizing dynamic actions and strategies in ever-changing environments. Deep learning brings sophisticated pattern recognition to complex data streams, critical for data-rich environments. Each section explains the technique's role, its importance for marine infrastructure, and how it fits into the multi-domain simulation. The chapter highlights how intelligent agents, digital twins, and distributed simulations work together to support adaptive maritime resilience (Bruzzone et al. 2021; Bruzzone, Longo & Massei 2023).

The chapter ends by showing how these AI methods together help with anomaly detection, risk assessment, operational improvement, and decision-making in

complex offshore systems. Their integration means the framework can provide not just analysis and diagnosis, but also prediction and guidance, letting operators, regulators, and planners test strategies in a realistic simulated environment.

8.0.1 Supervised Learning

Supervised learning is the most established and reliable machine-learning method used in the simulator’s decision-support system. It works well in areas where the marine environment shows repeatable patterns and where past data helps build models to classify states or predict changes. In the Strategic Engineering framework for this research (Bruzzone, Massei and Sinelschchikov 2021), supervised learning modules are placed in the analytical layers that interpret large amounts of sensor data from the simulation engine, the Marine Spatial Decision Interface (MSDI), and the cyber-physical communication layer.

In the context of offshore infrastructures, supervised learning plays a defining role in anomaly classification for structural, environmental, cyber-physical, and operational domains. Because the simulator includes high-fidelity representations of structural degradation, environmental stressors, and multi-domain vehicle operations, it is possible to train supervised models on labelled datasets generated directly from simulation runs. These datasets distinguish between normal operational states and flagged disturbances, enabling models to approximate real-world classification tasks. For example, the structural-monitoring components of the simulation produce time-series signatures reflecting fatigue accumulation, scour progression, or corrosion-related changes in material response elements fully grounded in validated engineering models (Bai, Marsden and Li 2021; Melchers and Jeffrey 2018). Using labelled simulation data, supervised classifiers learn to differentiate benign fluctuations from early indicators of structural anomalies.

This approach also applies to modeling marine robotics behavior. The simulator’s UAV, USV, and AUV units generate navigation paths and sensor data that change with sea conditions, bathymetry, vehicle health, and mission setup. Training supervised algorithms on these variations helps the system spot abnormal behavior, such as an AUV straying from its optimal path or a USV showing steering issues due to environmental factors.

The simulator’s multi-sensor fusion, based on previous maritime and industrial research (Massei and Bruzzone 2010; Gotelli et al. 2019), makes supervised models more robust by letting them learn from different data sources. Supervised learning also helps detect cyber-physical anomalies. Issues like communication problems, packet loss, latency spikes, and data inconsistencies are labeled during

training and then recognized in real time. This supports the goal of keeping the physical and cyber parts of offshore systems in sync, which is important in digital-twin and distributed simulation research (Jones, Snider and Njuguna 2020). In the HLA-based setup, supervised models act as diagnostic tools at the federate level, alerting the Intelligent Agent (IA) system when a risk appears.

Across all these applications, the integration of supervised learning strengthens the simulator’s capacity to provide early-warning intelligence, allowing inspection planning, vehicle coordination and maintenance scheduling to adapt dynamically to evolving conditions. It does so while remaining fully compatible with the strategic-engineering paradigm developed in the Genoa research community (Bruzzone et al. 2011; Bruzzone, Longo and Massei 2023).

8.0.2 Unsupervised Learning

While supervised learning relies on labeled data, unsupervised learning helps the simulator find patterns and anomalies when there are no prior examples. This is especially useful in marine settings, where unexpected behaviors and complex data are common. The simulator’s use of autonomous agents, multi-domain sensors, structural models, and communication systems creates varied data, making it ideal for unsupervised methods. In this framework, unsupervised learning methods serve three primary functions. First, they identify emergent operational clusters that reflect typical system behavior. For example, when clustering methods are applied to AUV navigation tracks, the system might identify a cluster characterized by consistent velocity and path regularity, which represents normal operational conditions for these vehicles. Conversely, a separate cluster indicating atypical velocity fluctuations could highlight potential issues requiring further investigation. By analyzing structural health indicators, turbidity cycles, communication-latency signatures, or vessel-traffic patterns, the system learns what typical ‘normality’ looks like without relying on predefined classifications. Deviations from these learned clusters then become signals of potential anomalies. This approach is consistent with research in maritime anomaly detection, where clustering methods reveal unexpected navigation patterns, environmental irregularities, or unregistered subsea activity (Ridao et al. 2018; Hughes Clarke 2018).

The second function concerns dimensionality reduction and latent-space exploration. Marine data streams from multibeam soundings to acoustic-modem metrics or digital-twin updates are often high-dimensional and exhibit complex correlations. Unsupervised algorithms extract the latent features that govern system behaviour, which in turn strengthens the interpretation capabilities

of the IA system. These latent variables allow the simulator to recognize shifts in environmental regimes, drifting operational baselines, or slow-building structural effects that may not appear anomalous on a single sensor channel. Such transformations contribute to more reliable multi-sensor fusion, echoing methodologies demonstrated in maritime SLAM, environmental reconstruction, and underwater perception research (Kinsey, Eustice and Whitcomb 2006; Jaffe 2015).

The third role is detecting new or unusual events in digital communication and cyber-physical systems. In complex networks, problems can come from unexpected combinations of delays, packet changes, bandwidth shifts, or node behavior. Since these issues are not always known ahead of time, unsupervised models help find new patterns. This is important for digital-twin consistency checks, where the IA must decide if differences between predicted and actual behavior are due to the environment, sensor drift, communication problems, or operational issues (Tao and Qi 2019).

In the HLA-based system, unsupervised learning units act as passive, always-adapting observers. They help the simulator spot weak signals, especially in long or complex scenarios with many interacting disturbances across air, sea, and cyber layers. By being part of the MSDI, they let operators notice small changes in vehicle coordination, infrastructure, or environment before these become bigger problems.

8.0.3 Reinforcement Learning

Reinforcement learning (RL) introduces a fundamentally different way of supporting decisions within marine inspection and protection systems. Whereas supervised and unsupervised methods infer patterns from historical data, RL produces adaptive behaviours by allowing an autonomous agent to interact with a simulated environment and learn operationally effective strategies through experience. In the context of offshore and subsea infrastructure, this paradigm is particularly compelling because inspection vehicles, support vessels, and multi-domain sensor networks operate in environments characterised by continuous dynamics, uncertainty, and high-dimensional decision spaces. RL therefore provides a principled approach for identifying action sequences that optimise inspection coverage, reduce mission risk, or sustain system performance under variable conditions.

RL works well in this field because of the Strategic Engineering framework behind the simulator. The simulation uses a distributed HLA-compliant system,

where each main asset like AUVs, USVs, UAVs, OSVs, environmental fields, digital twins, sensor networks, and cyber units acts as its own federate, sharing state updates through RTI. This setup fits RL, since the environment gives consistent state changes and rewards, and inspection actions are judged in realistic conditions. The system lets RL agents train in a multi-domain, physics-based environment that closely matches real marine operations, as shown in research on adaptive decision models for maritime domains (Bruzzone et al. 2011; Bruzzone et al. 2021).

Within this framework, RL supports a wide range of operational objectives. One example concerns optimisation of AUV inspection trajectories. Because subsea communication suffers from limited bandwidth and high latency, an AUV must often navigate with incomplete environmental information and energy constraints. RL enables the autonomous agent to explore inspection paths while receiving reward signals associated with inspection completeness, energy efficiency, risk minimisation, and avoidance of interference with other assets. Through iterative exposure to the simulated environment, the agent progressively identifies behaviours that maximise inspection reliability under prevailing constraints an approach also reflected in contemporary studies of long-endurance marine autonomy (Paull et al. 2018; Bingham et al. 2020).

RL also contributes to real-time asset coordination. When multiple inspection units operate simultaneously, the Intelligent Agent (IA) layer can incorporate RL-based policies that refine task allocation, sequencing, and cooperation. For example, a USV may reposition dynamically to serve as a communications relay for AUVs experiencing acoustic interference, or a UAV may adjust altitude and route based on predicted vessel traffic flows. These adaptive decisions rely on the RL agent's ability to recognise patterns in the environment through accumulated experience. The federated simulation supports this learning process by providing consistent interactions between physical assets, communication channels, and environmental disturbances, enabling RL to function within a controlled yet operationally realistic representation of the offshore domain (Gottelli et al. 2019). By adding RL to the Strategic Engineering simulation, the system can keep improving and refining its strategies on its own. RL agents can learn not just the best actions for normal situations, but also resilient behaviors that handle disturbances, sensor problems, or changing ocean and cyber conditions. This leads to decision-support policies that are based on evidence, tested in scenarios, and support the goal of predictive resilience in marine operations.

8.0.4 Deep Learning

Deep learning introduces a set of computational models capable of extracting high-level representations from large, heterogeneous datasets. This capability is especially relevant in offshore and subsea environments, where operational decisions depend on fusing complex information streams, such as sonar imaging, multibeam bathymetry, underwater video, turbidity and geochemical sensors, AIS traffic flows, structural health monitoring data, environmental forecasts, and cyber-physical telemetry. The ability of deep neural networks to recognise subtle, non-linear patterns within such multi-domain data makes them indispensable for anomaly detection, classification, and prediction tasks. The simulation environment offers plenty of training data for deep learning models, since the HLA/RTI system provides synchronized updates from all components. Data like sonar, images, bathymetry, motion, vibration, environment, and communication logs are available as live streams or recorded traces. This matches the Strategic Engineering approach, where simulation and real data work together to support strong AI-driven decisions (Massei & Bruzzone 2010; Bruzzone et al. 2021).

Deep learning has several important uses. Convolutional neural networks (CNNs) analyze underwater images and sonar from AUVs to find structural problems like corrosion, scour, coating damage, moved supports, or biofouling. CNNs trained on simulation data can later be used on real inspection footage, taking advantage of the controlled variety in the virtual environment. This matches current research in subsea imaging, where deep networks are leading in anomaly detection and classification (Jaffe 2015; Qin et al. 2018). Recurrent neural networks (RNNs), including LSTM models, are good at handling time-based changes in environmental and structural monitoring. Offshore assets face constant changes in load, vibration, pressure, temperature, and ocean forces. RNNs help the system spot time-based anomalies, like slow changes in strain, cycles in turbidity, or unusual acoustic backgrounds that could affect AUV navigation. These abilities fit with data-driven methods that use multi-sensor time-series for predictive maintenance (Fan & Luo 2021).

Deep learning also improves monitoring of cyber-physical consistency. Each simulated entity has a digital counterpart, so matching physical data with digital records is important. Autoencoders, graph neural networks, and hybrid models can find differences between expected and actual data, such as bad sensor readings, communication problems, or mismatched digital twins. This helps keep the simulation resilient, as smooth information exchange is key for operations (Jones et al. 2020). Importantly, addressing interpretability early can reassure users concerned about the 'black-box' nature of deep learning

8.1 Integration into the Strategic Engineering Framework

models. By employing methods like attention mechanisms or local interpretable model-agnostic explanations (LIME), operators can gain insights into how autoencoder detections are made, ensuring transparency and trust in the AI's findings.

Deep learning also works closely with RL and IA coordination. RL improves behavior through interaction, while deep learning boosts perception and prediction. For example, a CNN can spot a structural problem on a pipeline, and an RNN can predict how it might develop. The RL agent uses this information to change inspection plans, reroute AUVs, or set new priorities. This combination of learning methods has been widely studied in maritime and industrial simulations, where layered AI supports decisions at different times and scales (Bruzzone et al. 2020). Overall, deep learning supports the main goal of the Strategic Engineering framework: giving full situational awareness, early anomaly detection, and predictive insights across all marine operations. These methods turn scattered sensor and simulation data into useful information, helping the system enable proactive action, resilient management, and better decisions in uncertain situations.

8.1 Integration into the Strategic Engineering Framework

Integration into the Strategic Engineering Framework involves embedding AI and machine learning within the broader methodology to ensure coherent operation across all simulated marine environment domains. This process enables effective anomaly detection, decision support, and adaptive control. Strategic Engineering, as detailed by Bruzzone, Massei, Sinelshchikov, and collaborators, unifies modeling, simulation, data analytics, and human decision-making in a closed-loop, system-of-systems approach. AI and ML algorithms integrate into this framework, not as stand-alone modules, but as part of a coordinated architecture where real-world observations inform simulations, resulting in predictive insights on which Intelligent Agents (IAs) act in real-time (Bruzzone et al. 2021).

First, at the HLA/RTI layer, it serves as the formal interoperability backbone. Here, each AI-enabled module, such as supervised classifiers for structural anomalies, unsupervised models for behavioral pattern discovery, RL agents for planning optimization, or deep learning networks for sensor interpretation, operates as an HLA federate. This setup ensures strict time management, deterministic data exchange, and synchronization with the simulation engine. Consequently, AI modules can contribute decision-relevant outputs without violating causality or hindering multi-domain coordination. This interoperability

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model aligns with federated simulation principles long adopted in maritime and port-logistics simulation research (Bruzzone, Massei & Gotelli 2010; Bruzzone et al. 2011).

A second key integration point is the IA coordination layer. In this layer, ML models provide intelligence across varying horizons: supervised and deep learning models facilitate short-term anomaly detection; unsupervised methods enable mid-term pattern discovery; and reinforcement learning optimizes mission planning, maintenance cycles, and resource allocation for the long term. The IA framework synthesizes these outputs to maintain situational awareness, forecast hazard evolution, balance operational objectives, and dynamically adjust plans for UAVs, USVs, AUVs, and offshore support vessels. This aligns with modeling approaches in port-resilience and industrial-logistics simulations where intelligent agents mediate resource utilization and operational risk (Gotelli et al. 2019).

Integration also encompasses the digital twin layer. Here, sensor-derived data, including structural loads, acoustic signatures, vibration patterns, turbidity fields, or navigation telemetry, is continuously assimilated into the twin, recalibrating models of structural behavior, environmental evolution, and operational status. AI algorithms filter noise, validate sensor integrity, cross-correlate multi-domain information, and refine predictions. Related research on cyber-physical infrastructure highlights the importance of this continuous synchronization for predictive maintenance, early hazard identification, and operational continuity in offshore environments (Jones et al. 2020; Fan & Luo 2021).

Finally, the integration facilitates meaningful human–AI collaboration. AI models act as analytical extensions of human judgment rather than replacements for human expertise. Decision-makers interact with the outputs via the Marine Spatial Decision Interface (MSDI), which visualizes anomaly detections, probabilistic predictions, mission options, and confidence levels. This ensures compliance with the core requirements for traceability and interpretability within Strategic Engineering and international maritime standards, while avoiding over-automation.

Through these mechanisms, AI and ML become embedded, functional components of a coherent operational system, capable of supporting high-stakes, multi-domain decision-making across the entire life cycle of offshore and subsea infrastructure. This chapter has examined how AI and machine learning enhance anomaly detection, predictive assessment, and operational decision-making in distributed marine infrastructures. Through supervised detection models, the framework can identify known patterns of structural degradation, vessel behavior

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deviation, or sensor drift. Through unsupervised approaches, it uncovers emergent or previously unseen phenomena within large volumes of multi-domain data. Reinforcement learning contributes adaptive strategies for inspection routing, resource allocation, and long-term operational planning, while deep learning enables advanced interpretation of imagery, acoustics, and temporal sensor sequences.

In prior work on pandemics, ports and marine security, AI has been used for clustering accident types, risk scoring of vessels and optimizing patrol plans, always embedded within a Strategic-Engineering loop where simulation and real data mutually inform each other (Bruzzone et al., 2017)(Bruzzone et al., 2021). The same integration pattern is adopted here, using supervised and unsupervised methods to detect anomalies in multi-domain sensor streams and reinforcement-style planners to explore alternative inspection and protection policies in the simulation environment (Bruzzone et al., 2023).

Crucially, the thesis established how these AI techniques are not isolated analytical tools; they contribute to the Strategic Engineering methodology through federation within an HLA/RTI-driven distributed simulation; synergy with Intelligent Agents for coordinated decision-making; integration with the digital twin for continuous calibration; support for human supervisors through the MSDI interface; alignment with the real capabilities of the simulator and multi-domain marine environment.

By embedding AI within this broader architecture, the system supports a high level of resilience, situational awareness, and predictive capability. The resulting approach reflects the long-standing research lineage in maritime simulation, distributed modeling, and strategic decision support pioneered by Prof. Bruzzone, Dr. Massei, and collaborators. This chapter therefore provides the conceptual and methodological foundation for integrating intelligent anomaly detection and machine-learning-based decision support into the simulation of offshore energy systems, subsea assets, and autonomous multi-domain fleets.

8.2 XR-Enabled 3D-Printed Interactive Assets for Human–AI Decision Support

Combining Extended Reality (XR), Augmented Reality (AR), Virtual Reality (VR), and 3D-printed models is a key part of the decision-support system in this thesis. This subsystem links human operators with the multi-domain, AI-driven simulation in the Extended Maritime Framework. The aim is not just to display

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digital content, but to create an environment where users can understand, interact with, and review complex marine scenarios. This is important for strategic engineering, where clear thinking and interactive awareness are needed for planning, supervision, and evaluation of autonomous operations. The system is deliberately designed for multi-platform accessibility. Workstations serve as the analytical core, allowing operators to perform high-precision scenario analysis, monitor simulation states, and interact with the digital twin. Smartphones and tablets enable lightweight access to the same simulation environment, offering a portable and rapid interface suitable for field validation or distributed training. The SPIDER CAVE, acting as a Cave Automatic Virtual Environment (CAVE), provides a fully immersive representation in which operators can move inside a room-scale Spatial Decision Interface projection of the simulated offshore domain. This immersive environment significantly reduces briefing time by providing intuitive interaction with complex data, thereby enhancing understanding and decision-making efficiency. It supports collaborative interaction, enabling several participants to explore, discuss, and refine strategic decisions in real-time. Such multi-platform congruence allows decision-makers to transition between devices without losing context, maintaining continuity across spatially distributed planning sessions or multi-team operations.

A key feature of the system is the use of physical 3D-printed models within the XR environment. These models represent vessels, offshore structures, platforms, or subsea assets at scale. When viewed through an AR interface, the physical model combines real geometry with live simulation data. The AR system overlays operational states, anomalies, or environmental effects onto the model, helping users understand structural and spatial relationships more easily. This approach improves understanding of complex scenarios by combining hands-on interaction with real-time digital simulation.

The Virtual Interactive World brings these representations together in one environment. Here, users can see complex details like AUV paths, environmental changes, cable tensions, or structural deformations, and watch how autonomous agents work together. Unlike standard dashboards or 2D tools, this system provides a three-dimensional decision space that matches the structure of the Extended Maritime Framework. By showing air, surface, underwater, and cyber layers in one immersive setting, the XR framework helps users see the whole system and supports integrated thinking, which is important for strategic engineering.

The SPIDER CAVE plays a particularly important role within this ecosystem. It transforms the simulation into a navigable environment where full-scale digital

8.2 XR-Enabled 3D-Printed Interactive Assets for Human–AI Decision Support



Figure 8.1: XR-Enabled 3D-Printed Interactive Assets

8.2 XR-Enabled 3D-Printed Interactive Assets for Human–AI Decision Support

twins can be observed in motion, enabling a user to walk around, through, or above virtual infrastructure. This laboratory-grade immersive environment supports collaborative training, complex mission rehearsal, and cross-disciplinary discussions among engineers, operators, and analysts. By presenting Spatial Decision Interface information at a natural scale, the CAVE environment mitigates the perceptual distortions inherent in screen-based representations and enhances a user’s ability to perceive occlusions, spatial conflicts, inspection gaps, and navigational constraints. This feature is essential for multi-domain coordination, where the interplay between UAVs, USVs, AUVs, surface traffic, and subsea structures must be visualised as a single, coherent system.

These capabilities align with the principles of the Simulation Team’s long-standing work on immersive M&S environments for maritime and industrial systems, where XR interfaces are used not as visual ornaments but as functional components within an interoperable architecture (Massei and Bruzzone 2010; Bruzzone et al. 2011; Gotelli et al. 2019). The XR-integrated assets support the HLA-based federated simulation structure by presenting distributed simulation outputs within a unified perceptual space. The integration reinforces the human-in-the-loop requirement of MASS regulatory frameworks, ensuring that autonomy remains supervised through interfaces that promote transparency, interpretability, and operational traceability.

The practical interaction between digital and physical elements has additional methodological value. When operators handle 3D-printed models while observing XR-based overlays, they can perform direct spatial reasoning related to domain interactions, such as cable routing conflicts, vessel manoeuvring constraints, or AUV deployment angles. This is particularly relevant for scenario evaluation under uncertainty, where subtle geometric misalignments can lead to inspection failures or operational delays. Physical manipulation of models supports a deeper understanding of how the autonomous triad of UAV, USV, and AUV units interacts with marine infrastructures across the air, surface, and subsurface continuum. Imagine a maintenance team gathered around a 3D-printed model of a pipeline. As they rotate the model under XR overlays, they suddenly notice a clearance issue that was not apparent in digital-only simulations. The team members discuss and experiment with adjustments in real-time, guided by the tactile feedback and the digital data superimposed onto the model. This hands-on exploration leads to an immediate solution, illustrating the hybrid interface’s effectiveness in bringing complex scenarios to life. Such interactions not only streamline decision-making but also enhance comprehension of the operational domain’s intricacies.

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In practice, this hybrid XR and 3D-model approach supports training, reengineering, and emergency response. For example, a maintenance team can practice moving an AUV inspection pattern while seeing seabed features overlaid on a physical model. Environmental changes like turbidity plumes or shifting sediment can be shown directly in the user’s view. An operator reviewing a structural anomaly found by AI can look at the affected area on both the physical model and the digital twin, comparing predicted damage with historical data from the simulation. These interactions help strategic engineering workflows move smoothly between hands-on understanding and digital analysis.

XR-based systems for port safety and industrial plant training show that tangible and immersive interfaces make complex AI-generated insights more understandable and actionable for operators (Bruzzone et al., 2023). Building on these findings, the Marine Spatial Decision Interface links XR views and interactive assets to AI-driven indicators and simulation states, enabling users to interrogate anomalies, visualize risk propagation and co-design mitigation actions while maintaining human control over decisions (Bruzzone et al., 2024).

The integration of multi-platform access, immersive XR environments, and physical 3D-printed assets results in a system with high usability and interpretability. These features enhance decision-making, improve training fidelity, and enable ongoing evaluation of resilience within the multi-domain maritime environment. The interface serves as a core component of the human–AI collaborative architecture, supporting comprehensive management of the complexities associated with autonomous maritime inspection systems. Future work should focus on scaling these advances for real-time offshore deployments, necessitating further exploration and validation of the framework in operational settings to facilitate practical applications and drive innovation in maritime operations.

Chapter 9

Conclusions

This thesis builds a strategic-engineering framework that strengthens the resilience, maintainability and operational continuity of marine infrastructures by means of modeling and simulation of complex scenarios. It examines the systems such as the subsea cables, the energy platforms and the distributed autonomous fleets. The offshore systems work in the environment where natural, operational and cyber-physical disruptions mix in ways that're complex and unpredictable. At the same time traditional engineering approaches that examine these challenges in isolation and at fixed points, in time are no longer enough. This work addresses this gap by introducing a dynamic, model-driven methodology that integrates extended reality, advanced simulation, intelligent agents, and multi-domain sensing into a unified decision-support ecosystem.

At its core, the thesis establishes that resilience in the maritime domain cannot be achieved by focusing on a single platform, sensor, or operational procedure. Instead, resilience must be understood as a property emerging from the coordinated behavior of an entire system-of-systems spanning the air, surface, underwater, coastal, space, and cyber domains. To capture this complexity, the research employs high-fidelity modelling and simulation supported by digital-twin logic and multi-agent coordination.

These tools enable exploration of thousands of scenarios, ranging from inspection and maintenance to unexpected hazards, while continuously evaluating performance, wear, and recovery. Indeed, these tools were applied to evaluate system responses across varied scenarios. One important part of this work is the development of multiple domain scenarios that use Intelligent Agents (IAs). These agents act as reasoning elements inside the simulation. The agents enable task allocation, danger detection and flexible mission planning, across different fleets of autonomous systems such as UAVs, USVs and AUVs. Through this

capability, the system transitions from a static planning tool to an adaptive, real-time environment capable of revealing how different strategies perform under compounding disruptions.

Another major innovation lies in the integration of Extended Reality (XR) technologies in addition to traditional computer interfaces, including Extended Reality environments such as the HoloLens used in coordination with 3D-printed physical models. This multi-modal interface allows human operators, analysts, and trainees to interact with complex simulated environments in intuitive and spatially coherent ways. By enabling the simultaneous exploration of virtual and physical representations of offshore assets, the framework enhances understanding, reduces cognitive load, and supports collaborative decision-making. The XR interface becomes an essential bridge between human oversight and autonomous system behavior, aligning with regulatory expectations for human-in-the-loop supervision in complex maritime operations.

The methodology also incorporates AI-driven anomaly detection and decision-support mechanisms. Through supervised, unsupervised, reinforcement, and deep learning approaches, the system interprets multi-domain data streams, identifies early signs of structural or operational anomalies, and proposes optimized responses. These algorithms operate alongside the simulation to form a tightly integrated analytical environment capable of assessing feasibility, reliability, robustness, and long-term sustainability of different strategies. In practical terms, the thesis demonstrates that combining XR, M&S, and AI/IA within a strategic-engineering framework enables unprecedented flexibility for testing new assets, operational concepts, and procedural innovations. Stakeholders can evaluate how changes propagate through an interconnected offshore environment and understand the cascading effects of disruptions before they occur in reality.

This approach strengthens risk management, supports proactive maintenance planning, and improves the ability of operators to respond to both expected and unexpected events. Overall, the research establishes a new paradigm for the design, evaluation, and governance of complex marine systems. By merging advanced simulation technologies, intelligent autonomy, and immersive human interfaces, it provides a rigorous and forward-looking foundation for enhancing the resilience and security of strategic offshore assets in an increasingly uncertain world.

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