

Article

A Governance-Aware Methodological Framework for Cognitive AI Integration in Marine CAD: A Conceptual Pipe Routing Use Case

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Abstract

This paper proposes a governance-aware methodological framework for the integration of Cognitive Artificial Intelligence into marine CAD environments. Unlike existing approaches that focus on isolated optimization or prediction tasks, the proposed framework introduces a structured architecture combining engineering knowledge corpora, hybrid AI reasoning, and CAD-based interaction within a traceable and regulatory-aware workflow. The contribution of this work is methodological rather than domain-exhaustive. The framework is illustrated through a conceptual pipe routing use case, selected as a representative high-constraint design subsystem involving spatial reasoning, compliance verification, and iterative coordination. A normalized performance evaluation model is defined to estimate improvements in design efficiency, convergence, compliance validation and rework reduction. Although the validation is conceptual, the results are consistent with reported improvements in AI-assisted engineering workflows. The proposed framework gives a basis for integrating AI into marine CAD environments, aligned with newer digital ship design and Shipyard 4.0 approaches.

Keywords: ship design; CAD; machine learning; naval architecture; artificial intelligence; cognitive engineering; CAD integration; pipe routing; knowledge graph; Shipyard 4.0; hybrid AI systems

1. Introduction

Ship design has become a complex, multidisciplinary engineering process requiring the coordination of structural, mechanical, electrical, safety and production constraints. Modern vessels must satisfy classification rules, owner specifications, environmental regulations and lifecycle efficiency targets. While advanced Computer-Aided Design (CAD) systems have improved geometric modeling, decision-making remains largely manual and iterative.

The integration of Artificial Intelligence into ship design processes is still limited despite significant advances in digital engineering technologies. The lack of structured methodologies that combine AI capabilities with engineering knowledge, regulatory constraints and CAD-based workflows represents a barrier to practical use in marine design environments.

This work tackles this gap by proposing a governance-led method for integrating Cognitive Artificial Intelligence into marine CAD environments.



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The integration of AI into engineering design is not only a technical challenge but also a systems integration problem involving knowledge, processes and governance.

Naval architecture and shipbuilding are traditionally multidisciplinary fields combining hydrodynamics, structural mechanics, propulsion, materials science and production engineering (see Figure 1). The increasing complexity of modern ships, combined with stricter environmental regulations and economic constraints, has motivated the adoption of advanced computational tools to enhance design efficiency and operational performance.

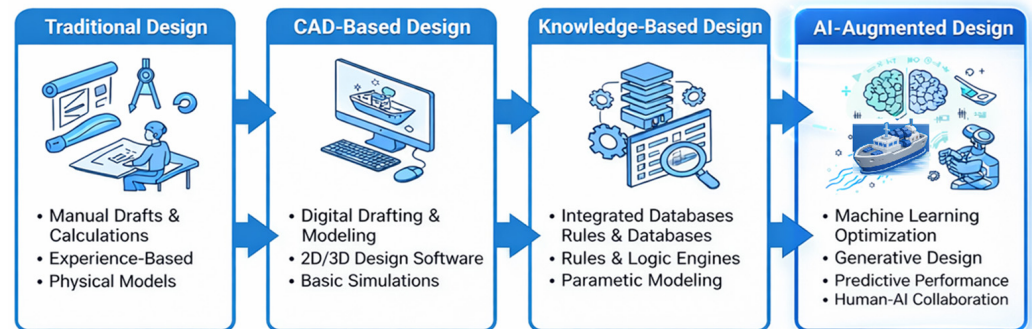


Figure 1. Evolution of ship design paradigms from craftsmanship to intelligent autonomy.

Artificial Intelligence (AI) has emerged as a technology able to address nonlinear, multi-objective and data-intensive problems. Unlike classical numerical approaches, AI techniques can learn patterns from historical and operational data, which allows for predictive and adaptive decision-making [1]. In the maritime sector, AI has started to show up for hull form optimization, fuel consumption prediction [2], machinery fault diagnosis, autonomous navigation and shipyard automation.

The technologies that are a key factor in the fourth industrial revolution are being consolidated over time. In this particular situation, the marine engineering sector is moving through a slow and uncertain change process, largely because it has little choice. The key question of this digital transformation is how to choose the best strategy, and how to measure your success on it.

When talking about digital transformation, several elements and exercises make up a workable strategy. To evaluate this process, it is necessary to define the right **Key Performance Indicators (KPIs)**, which are particular to each business or process. Of course, profit must be one of these KPIs for success, but good practices should follow along the transformation process to achieve this goal.

According to a report from McKinsey [3], less than 30% of the businesses embarked on this change succeed. Given the expectations, there is a 45% probability to get less revenue than anticipated [4].

When talking about the digital transformation of a company, it is not only important to select the best technologies to introduce but also how they are implemented.

The marine industry has tight margins but, on the contrary, requires high investments and risks. Accordingly, investments must be carefully selected, ensuring minimum risks. With that in mind, a clear understanding of the technologies to deploy and the precise problem to solve must be achieved.

Complementing the sustainability review of Ramírez-Peña et al. [5] discussed above, the same research group [6] proposed a conceptual model for a sustainable shipbuilding supply chain under an Industry 4.0 perspective, mapping established supply-chain sustainability paradigms onto the specific technologies and constraints of shipbuilding.

This work presents different solutions to improve ship design, applying different technologies such as **Data Analytics (DA)**, **Machine Learning (ML)** and AI. It is also worth

noting that these technologies are, according to QinetiQ, Southampton University and Lloyd's Register, highlighted in the near term in the Maritime Industry.

What this work adds is the definition of a governance-led method for integrating Cognitive Artificial Intelligence into marine CAD environments used in ship design. Unlike studies that focus on isolated algorithms or optimization techniques, this research puts forward a clear setup that links engineering knowledge corpora, hybrid AI reasoning mechanisms and interactive CAD interaction in a traceable and regulatory-compliant workflow.

The framework is specifically designed to address complex multidisciplinary design problems such as pipe routing, where spatial constraints, regulatory requirements and engineering heuristics interact at the same time. The proposed methodology sets out a layered architecture, a human-in-the-loop decision cycle and a normalized performance evaluation model that lets us estimate AI-assisted engineering processes.

This work does not aim to develop new optimization algorithms. Instead, it focuses on the integration of AI, engineering knowledge and CAD environments in a governance-led and traceable framework. This integration tackles a gap in current research, which remains largely fragmented and algorithm-centric.

Scope and Limitations of This Study

This paper does not aim to address ship design as a whole, nor to provide a solution to the range of problems involved in ship design and production. Instead, it focuses on the definition of a governance-led method for integrating Cognitive Artificial Intelligence into marine CAD environments.

This work tries to close a gap between AI capabilities and their practical use in regulated engineering environments, particularly in ship design, where traceability, compliance and integration in CAD workflows are essential.

The proposed framework is illustrated through a conceptual pipe routing use case, selected as a representative high-constraint engineering task. Pipe routing involves spatial reasoning, rule-based constraints, compliance verification and iterative design processes, making it suitable for demonstrating the interaction between AI, engineering knowledge and CAD systems.

Therefore, the contribution of this work lies in methodological integration rather than in solving specific ship design problems at full scale. Future work will focus on extending the framework to additional subsystems and validating it in industrial environments.

2. State of the Art of AI

The application of AI in marine engineering and ship design has undergone a transformation over the past few decades, evolving from early rule-based expert systems to advanced cognitive and learning-driven approaches. Initially, AI in ship design focused on expert systems that codified heuristic knowledge for hull form optimization, layout planning and preliminary design checks. These early systems, while useful, were limited by their rigidity and inability to adapt to complex, evolving design constraints. Modern approaches, by contrast, leverage ML, **Deep Learning** (DL) and cognitive AI to provide adaptive, context-aware decision support CAD environments. Machine learning algorithms such as Support Vector Machines, Random Forests and Gradient Boosting are now used to predict design parameters, assess performance and anticipate potential conflicts in multidisciplinary ship systems [7]. Deep learning techniques, including Convolutional Neural Networks and Graph Neural Networks, allow for spatial reasoning over complex 3D CAD models, supporting tasks such as collision detection, automated routing and layout optimization [8]. Cognitive AI extends these capabilities by combining symbolic knowledge representation with learning-based reasoning. Ontologies and knowledge graphs encode

ship-specific design rules, safety regulations and domain heuristics, which lets us use AI systems to provide design recommendations that are both informed by domain expertise and adaptable to new design scenarios.

One of the most critical applications of AI in ship design is pipe routing [9], a task characterized by spatial complexity, regulatory constraints and multidisciplinary dependencies. AI methods facilitate path planning for piping networks, optimizing routes while avoiding collisions, minimizing material usage and maintaining operational constraints such as slope and pressure limits. Classical graph-based algorithms such as Dijkstra and A* have been enhanced with reinforcement learning agents able to autonomously navigate CAD environments, explore alternative routes and learn from previous design instances. Constraint handling has also become more sophisticated, with AI systems integrating regulatory, safety and manufacturability requirements through constraint satisfaction problems and hybrid optimization techniques. These capabilities allow designers to generate feasible pipe layouts efficiently while adhering to strict classification society and international safety standards. Modern commercial CAD platforms, including Design Center NX®, increasingly embed AI modules that provide interactive recommendations, interactive layout generation and automated validation, supporting a collaborative human–AI design workflow.

Recent research trends highlight the integration of AI with digital twins, which lets us obtain continuous monitoring and simulation of ship systems, predictive maintenance and adaptive design updates. Human–AI collaboration is emphasized, with cognitive systems functioning as intelligent assistants that combine algorithmic optimization with human creativity and domain expertise. Explainable AI methods have gained prominence, giving interpretable reasoning for routing choices and design decisions, thereby increasing trust and regulatory acceptance. Multi-agent and distributed AI frameworks further enhance design exploration by simulating multiple subsystems concurrently, which is particularly valuable in congested ship compartments with overlapping routing challenges. Despite these advances, several limitations remain. High-quality, high-fidelity datasets for ship interiors and piping systems are scarce, limiting the effectiveness of supervised learning approaches. Computational demands remain high due to the complexity of large-scale 3D CAD models and multi-system interactions. Regulatory compliance continues to pose challenges, as AI-generated solutions must align with stringent international standards and classification society rules. Additionally, human acceptance can be an obstacle if AI recommendations are perceived as opaque or contrary to designer expertise.

The state of the art shows a clear progression from rigid, rule-based systems to cognitive, learning-driven and collaborative AI methods. These technologies provide significant potential for optimizing ship design processes, particularly in pipe routing, by improving efficiency, compliance and design creativity. The integration of AI promises to transform marine CAD environments into cognitive systems that support designers with adaptive reasoning, intelligent decision support and automated optimization, though challenges in explainability, computational efficiency and data accessibility must be carefully addressed to fully realize this potential.

To set the groundwork for the application of 4.0 technologies in the ship design sector, specifically for the use case detailed in this paper; the following section describes the state of the art of AI.

The following image, Figure 2, summarizes a common view of diverse technologies and the relation among them:

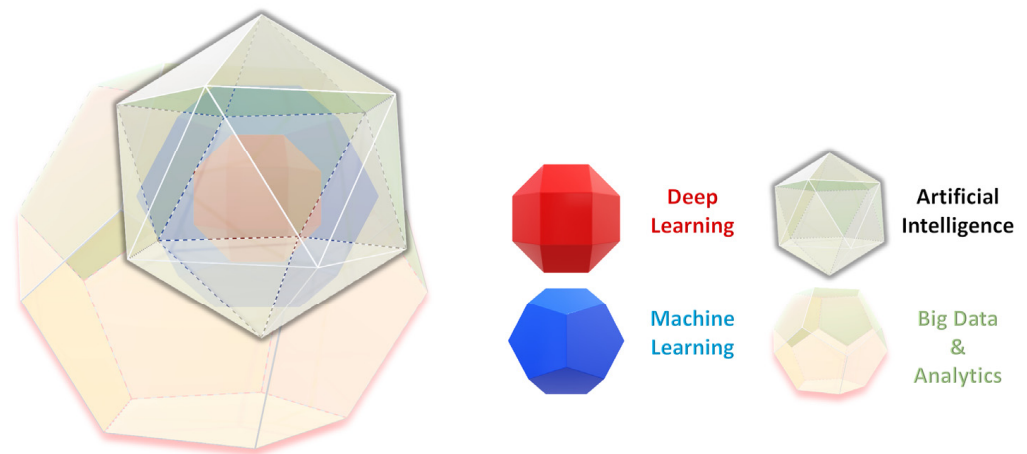


Figure 2. Relationships among big data and analytics, AI, ML and DA.

Although it was originally conceived as the science of producing technologies able to emulate human behavior, AI has become a broad field encompassing a broad spectrum of computational and mathematical methodologies. AI is no longer limited to symbolic reasoning or logic-based problem solving; it now integrates optimization, probabilistic modeling, pattern recognition and predictive analytics. The development of AI relies on mathematical foundations such as linear algebra, calculus, probability theory and graph theory, which enable machines to process, interpret and learn from large amounts of data. These computational frameworks are essential for designing intelligent systems able to autonomous decision-making, adaptive learning and cognitive reasoning. In practical applications, AI has been employed to model human-like cognition in engineering tasks, from design automation to simulation-based decision support. Within marine CAD environments, AI facilitates the understanding of spatial constraints, regulatory requirements and multidisciplinary interactions, giving tools that not only automate repetitive design processes but also generate optimized solutions in areas such as pipe routing, hull design and system layout planning. By integrating AI with domain-specific knowledge, modern ship design systems can achieve a higher degree of precision, efficiency and adaptability, bridging the gap between human expertise and computational intelligence.

DA, also commonly referred to as Data Mining, represents a field dedicated to extracting meaningful insights from raw and structured data by identifying patterns, correlations and trends [9]. In engineering applications, DA is for transforming the vast volumes of information generated during the design, construction and operational phases of ships into actionable knowledge. The process typically involves data collection, cleaning, integration, transformation and modeling, followed by the extraction of patterns and derivation of predictive insights. Modern DA techniques include statistical analysis, clustering, classification, regression and association analysis, each of which contributes to informed decision-making. In marine CAD environments, DA enables the evaluation of historical design data, performance simulations and operational feedback to optimize system layouts, minimize design conflicts and anticipate maintenance needs. By uncovering latent relationships in complex design data sets, DA forms the foundation upon which machine learning and AI algorithms can operate, ensuring that intelligent systems are both data-driven and context-aware. DA allows engineers to quantify uncertainty, validate design hypotheses and support risk-informed decision-making, which is particularly crucial in safety domains like ship design.

Machine Learning (ML) is a part of Artificial Intelligence (AI) focused on enabling systems to learn from data, detect patterns, and generate decisions or predictions without being explicitly programmed for each specific task. ML techniques support the extraction

of knowledge from datasets, making it possible to develop models capable of generalizing beyond the samples observed during training.

Key approaches in ML include supervised learning, where models learn from labeled datasets to make predictions; unsupervised learning, which identifies inherent structures or clusters in data; and reinforcement learning, where agents learn optimal strategies through trial-and-error interactions with their environment. Specific algorithms widely used in engineering and CAD applications include Support Vector Machines (SVMs) for classification and regression, Bayesian networks for probabilistic inference and clustering techniques for grouping similar design patterns, and association with rule learning for discovering relationships among design variables. DL, an advanced branch of ML, leverages multi-layered neural networks to model complex, high-dimensional data, making it particularly effective in tasks such as image recognition, 3D spatial reasoning and automated feature extraction from CAD models. In the context of marine CAD environments, ML and DL provide powerful tools for predictive maintenance, layout optimization, collision detection and automated pipe routing. By combining ML algorithms with cognitive reasoning and domain knowledge, ship designers can accelerate the design process, reduce errors and explore alternative solutions efficiently, achieving outcomes that closely emulate expert human decision-making while maintaining computational scalability. Figure 3 clarifies in detail most of the analysis contained inside ML.

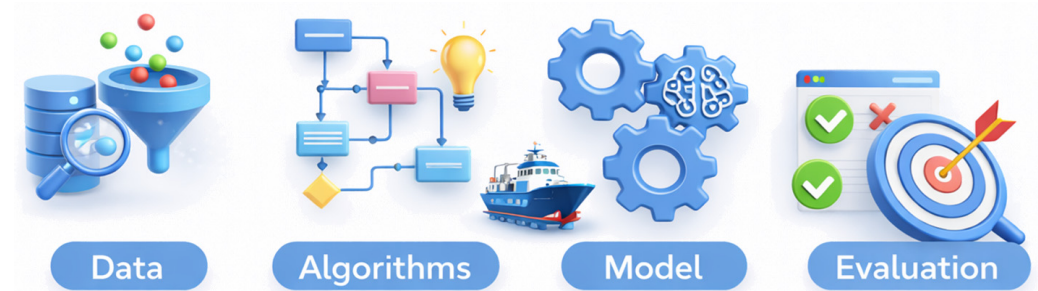


Figure 3. Principal Machine Learning (ML) elements.

Conceptually, ML is the evolution of rule-based systems, being able to distinguish among valid and surplus data, as well as deducing new rules not previously programmed.

During the last years, ML analyses have concentrated on DL, high-level difficulty algorithms which imitate human rationale.

The application of AI techniques in naval architecture has grown in recent years, especially in tasks with large search spaces and multiple objectives and constraints (cost, weight, performance, regulations and constructability) [10]. In parallel, publications are attempting to clarify the landscape through state-of-the-art reviews, highlighting the potential of data-driven approaches to accelerate design iterations, but also pointing out the lack of explicit methodological guidelines connecting these advances to industrial processes.

More recently, contributions have emerged discussing the integration of AI into marine project management and execution environments, reinforcing the idea that AI's impact is not only algorithmic, but also organizational and methodological throughout the design and engineering lifecycle.

There is a growing body of work on what AI can do in marine design, but the leap from the algorithm to how it is repeatably integrated into CAD (including manufacturing and engineering) remains the bottleneck.

AI Applications in Ship Design: Recent Contributions

Recent contributions in ship design research confirm the increasing relevance of Artificial Intelligence and digital-transition methodologies. The proceedings of the International Marine Design Conference [11] highlight several developments in this direction.

Grech La Rosa et al. [12] explored the application of generative AI in concept ship design, demonstrating its potential as a support tool for early-stage layout generation and design reasoning. Ha et al. [9] proposed an automated pipe-routing approach in ship unit modules, combining expert knowledge and optimization techniques. Karakostas and Antonopoulos [1] introduced knowledge graph structures to support ship digital twins, which lets us obtain structured engineering knowledge representation. Additionally, Koelman et al. [7] addressed the integration gap between early and detailed ship design through improved data models and workflow continuity.

These contributions reinforce the need for structured frameworks that integrate AI techniques with engineering knowledge, regulatory constraints and CAD-based workflows, which is the focus of the methodology proposed in this work.

Despite the growing body of research on AI applications in ship design, most approaches remain focused on isolated problems such as optimization, prediction, or simulation. There is a lack of integrated frameworks that combine engineering knowledge, AI reasoning and CAD environments in a governance-led and traceable workflow. This gap is particularly in regulated domains such as ship design.

3. Regulatory AI Framework in Marine Engineering

To transform regulatory documentation into an actionable corpus for cognitive systems, the literature on regulatory compliance and automated regulatory analysis is fundamental. Approaches combining ontologies and Natural Language Processing (NLP) to analyze regulatory documents and detect inconsistencies or normative structures are observed.

Likewise, proposals are newer that map regulatory terms and requirements to knowledge graphs, giving repeatable mechanisms to connect normative texts with formal structures. Contributions to legal compliance using NLP and graphs are also appearing, reinforcing the relevance of this approach for regulated domains (see Figure 4).

The AI Act is the first European regulatory framework specifically designed to regulate the use of AI. Its aim is not to stifle innovation, but to establish clear rules to ensure that AI systems are used safely, transparently and in accordance with human rights. In an industrial context, applying the EU AI Act reflects the complexities of the processes it seeks to regulate. Judging an AI system against the Act's criteria requires knowledge of the AI in the system as well as the industrial process or asset it affects, legal knowledge and assurance expertise.

There is a Standardization Request issued by the European Commission to develop harmonized standards to support the implementation of the AI Act based on:

- Trustworthiness framework.
- Risk management.
- Quality management system.
- Bias management.
- Quality and governance of datasets.
- Cybersecurity.
- Conformity assessment.

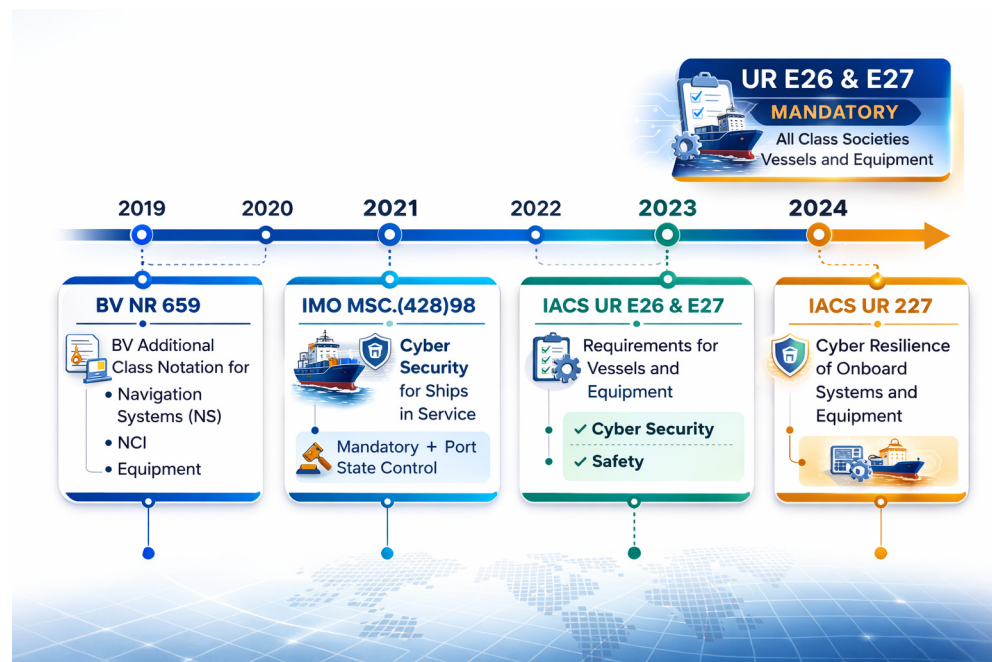


Figure 4. Evolution of AI regulations in the marine sector.

From the regulatory scheme, a risk-based approach for the governance of AI systems is provided, classifying them into different categories, as shown in Table 1.

Table 1. The governance of AI systems through a risk-based framework, which categorizes them according to their potential impact and associated risks.

Minimal Risk (e.g., Spam Filtering)	No Measures Necessary
Limited risk (e.g., chatbots)	Transparency measures
High risk (e.g., AI-based collision avoidance systems)	Strict risk management, transparency, documentation and data governance, plus human oversight measures
Unacceptable risk (e.g., social scoring)	Prohibited under European law

3.1. Machine Learning and Deep Learning

ML algorithms, including SVM, decision trees and Artificial Neural Networks (ANNs), are widely used for regression and classification problems in marine engineering. DL, particularly Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), enables high-dimensional feature extraction from complex datasets such as Computational Fluid Dynamics (CFD) results or sensor measurements. Those techniques are embedded in the data-processing step in the AI cycle (Figure 5):

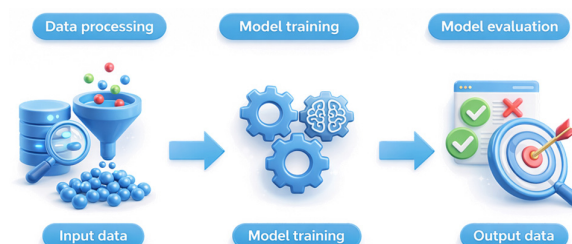


Figure 5. The data processing step in the AI workflow involves collecting, cleaning and transforming raw data into a structured format suitable for analysis and model training.

In NI 692, Bureau Veritas gives guidelines and recommendations for the assessment of machine learning systems in marine environments, structured according to the standard machine learning lifecycle (Figure 6). These guidelines outline an approach for evaluating the design, development, deployment and monitoring of AI-based systems onboard ships or in ship design processes. By following the lifecycle framework, the assessment covers key phases including data collection and preprocessing, model training and validation, performance evaluation and continuous monitoring during operational use. The recommendations also emphasize risk management, safety compliance and transparency, ensuring that AI systems meet both regulatory requirements and operational reliability standards. This structured methodology allows designers and engineers to implement machine learning solutions with confidence, giving a clear path from conceptual development to practical application while maintaining adherence to international maritime safety standards.



Figure 6. Implementation of ML systems in marine environments following the standard ML lifecycle.

3.2. Evolutionary and Optimization Algorithms

Evolutionary and optimization algorithms, including Genetic Algorithms (GAs), Particle Swarm Optimization (PSO) and multi-objective evolutionary algorithms, have become standard tools in ship design optimization. These algorithms enable designers to efficiently explore large and complex design spaces, balancing multiple performance criteria such as weight, stability, hydrodynamic efficiency and material cost. By iteratively generating and evaluating populations of design alternatives, these methods can identify near-optimal solutions that might be difficult or impossible to find through conventional trial-and-error approaches. In marine CAD environments, evolutionary algorithms are particularly effective for tasks such as hull form optimization, compartment layout planning and pipe routing, where spatial constraints and conflicting objectives require simultaneous consideration. Multi-objective evolutionary approaches allow designers to examine trade-offs explicitly, giving a set of Pareto-optimal solutions that can be evaluated according to operational priorities or regulatory requirements.

3.3. Physics-Informed and Hybrid Models

Recent research highlights the advantages of physics-informed and hybrid modeling approaches, which integrate AI methods with traditional physics-based models. Physics-Informed Neural Networks (PINNs), for example, embed governing equations and physical laws directly into the learning process, improving model generalization and interpretability while reducing the reliance on large datasets. These hybrid approaches are particularly valuable in marine engineering, where experimental or operational data may be limited or costly to obtain. By combining AI-driven learning with physics-based constraints, designers can ensure that predictions and optimizations remain physically consistent and reliable. Applications include fluid dynamics simulations, structural behavior prediction [13] and pipe flow analysis, where hybrid models (Figure 7) support faster, more accurate decision-making [14,15]. Such approaches bridge the gap between purely data-driven AI and classical engineering methods, offering a framework for cognitive ship design systems able to generating innovative yet feasible solutions.

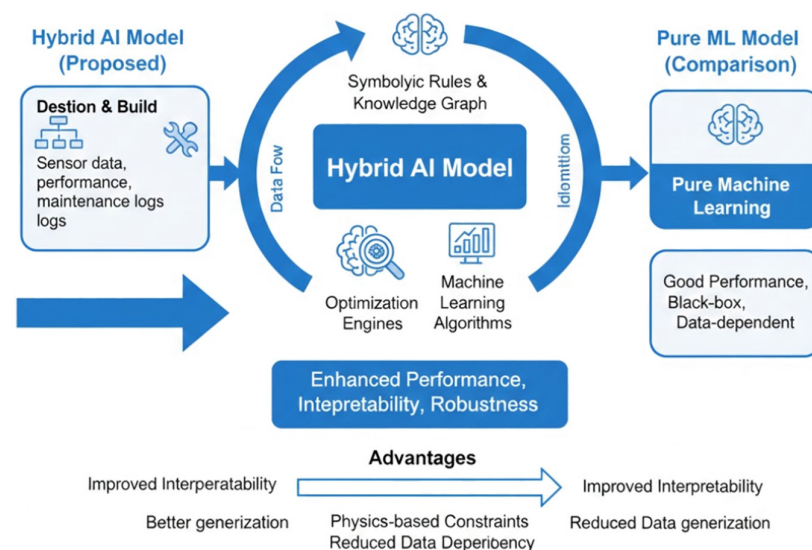


Figure 7. Hybrid AI model for engineering applications combining symbolic IA, Machine Learning and Optimization.

4. AI Applications in Ship Design and Operation

This research adopts a design-oriented methodology focused on system-level integration rather than isolated algorithmic innovation. The approach defines a layered architecture, structured workflow phases and quantitative evaluation metrics. Implementation stages include problem framing, corpus structuring, constraint formalization, hybrid model development, CAD embedding, validation and governance auditing [16].

Table 2 presents a comparative analysis of AI integration in ship design and broader engineering CAD environments. The table synthesizes contributions from the literature by highlighting the author and year, the application domain, the main AI technique employed, the level of integration in the CAD workflow, the degree of traceability provided and the limitations identified in each study. This structured overview allows readers to quickly evaluate trends across different sectors, such as the marine industry and complex engineering environments like Engineering, Procurement and Construction (EPC) projects and to understand how AI methods, from rule-based and optimization algorithms to machine learning and cognitive AI, are applied in practice. Key insights from the table include the varying degrees of integration achieved, the challenges related to transparency and

regulatory compliance, and recurring gaps that emphasize the need for a formal method for cognitive AI deployment in ship design [17].

Table 2. Representative AI applications in ship design and marine engineering.

Ref.	Authors (Year)	Domain	Technique	Integration Level	Governance /Traceability	Limitations
[14]	Kim et al. (2013)	Pipe routing	Optimization	Low	No	Limited CAD integration
[9]	Ha et al. (2024)	Pipe routing	Heuristic + expert rules	Medium	Partial	Module-level focus
[12]	Grech La Rosa et al. (2024)	Concept design	Generative AI	Low	No	Early-stage only
[1]	Karakostas & Antonopoulos (2024)	Digital twin	Knowledge graphs	Medium	Partial	Limited CAD integration
[7]	Koelman et al. (2024)	Design integration	Data models	Medium	Partial	No AI reasoning layer
[8]	Zhang (2022)	Hull optimization	Deep learning	Low	No	Isolated optimization
[15]	Yang et al. (2024)	Ship resistance	Machine learning	Low	No	Single-domain focus
[16]	Ruiz et al. (2023)	Maritime AI	Machine learning	Medium	Partial	General scope
[17]	Gupta et al. (2022)	Ship performance	Machine learning	Medium	Partial	Monitoring-focused
[5]	Ramírez-Peña et al. (2020)	Shipbuilding 4.0	AI systems	Medium	Partial	Framework-level
[18]	Cepowski (2020)	Ship performance	Neural networks	Low	No	Limited integration
[19]	Dong et al. (2022)	Pipe routing	Ant colony optimization	Medium	No	Algorithm-centric
[13]	Tsai et al. (2022)	Routing	AR + BIM	Medium	Partial	Construction-oriented
[20]	Wang et al. (2022)	MEP systems	Graph-based methods	Medium	Partial	Not naval-specific
[10]	Chandrasekhar & Suresh (2021)	Design optimization	Neural networks	Low	No	Limited CAD integration

The comparison highlights that existing approaches are predominantly algorithm-centric, with limited integration into CAD environments and minimal consideration of governance and traceability aspects. Reference numbers in the Ref. column above correspond to the numbered bibliography at the end of this manuscript, ensuring full traceability between the summary table and the full citations.

Table 2 summarizes representative and traceable contributions related to AI applications in ship design, routing optimization and marine engineering workflows. Only explicitly referenced and verifiable sources are included.

Beyond the marine sector, research and industrial practice have explored integrating advanced automation into CAD, particularly in complex engineering environments such as EPC projects. A trend toward using AI to enhance workflows and decision-making has been observed, though many recent studies remain exploratory, highlighting the need for a formal method.

Also relevant is the evidence from other domains (automotive, aerospace) where routing and automatic layout generation have been addressed through frameworks to make them adoptable by designers; this work serves as an analogy to argue that adoptability and the process are as important as the quality of the algorithm [5]. Outside the marine sector, Wang et al. [20] addressed a closely related compliance-checking problem for Mechanical, Electrical and Plumbing (MEP) systems in building information modeling (BIM). Their framework extracts MEP components from a BIM model, represents them as nodes and relationships in a graph database, encodes the applicable connection rules as a knowledge graph, and verifies compliance through subgraph matching. This offers a directly transferable pattern for the corpus-to-CAD rule-checking mechanism proposed in Section 4.7 of this work.

There are clear signs of convergence toward AI-augmented CAD, but a replicable architecture and methodology that connect regulatory knowledge, historical data and interactive feedback in CAD are still lacking.

4.1. Hull Forms Design and Optimization

Hull forms optimization is one of the most mature AI application areas in naval architecture [18]. AI-based surrogate models clearly reduce computational cost compared to traditional CFD-based optimization (Figure 8).

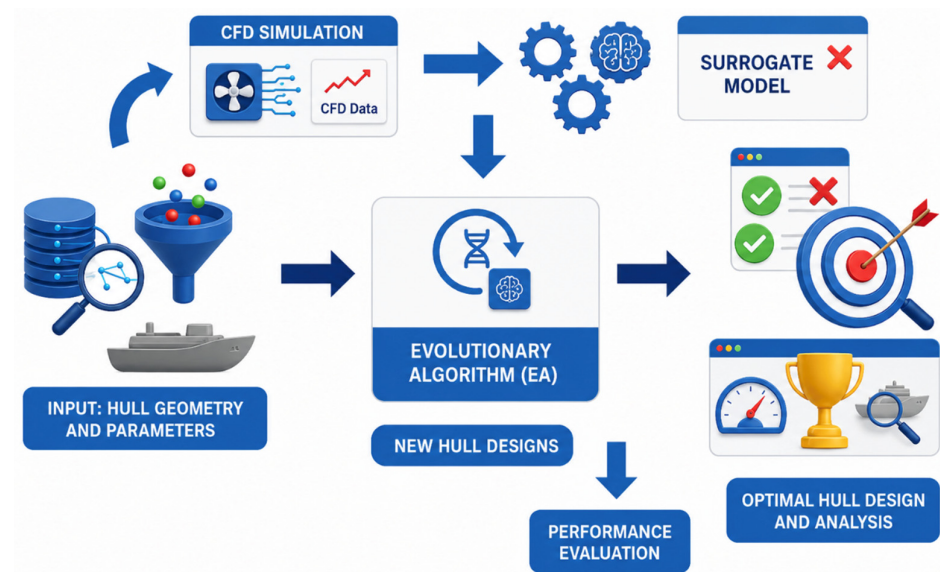


Figure 8. Workflow of AI-assisted hull form optimization bringing CFD data and surrogate models together, with evolutionary algorithms.

Zhang, in [8], demonstrated the use of deep learning models to predict hydrodynamic performance and guide hull shape optimization, achieving comparable accuracy to CFD simulations with clearly reduced computation time. Similar approaches have been reported using genetic algorithms for multi-objective trade-offs between resistance, stability and seakeeping [17].

At the preliminary design stage, Cepowski and Chorab [21] derived predictive design formulas for container ships using a database of vessels built since 2015, comparing artificial neural networks against multiple nonlinear regression with randomly searched functions. Both approaches yielded estimates of comparable accuracy for principal dimensions—length between perpendiculars, breadth, moulded draught and depth—as functions of deadweight, TEU capacity and design speed.

4.2. Structural Health Monitoring and Predictive Maintenance

AI-driven predictive maintenance has become more important due to the increasing availability of onboard sensor data [22]. Neural networks and reinforcement learning algorithms are used to detect anomalies, predict fatigue damage and estimate Remaining Useful Life (RUL) of structural components and machinery.

Chen et al. applied AI-based structural health monitoring techniques using optical fiber sensors to marine structures, demonstrating early damage detection capabilities superior to traditional threshold-based systems [23]. Reinforcement learning has also been employed for predictive maintenance of marine main engines (Figure 9), optimizing maintenance schedules and reducing downtime.

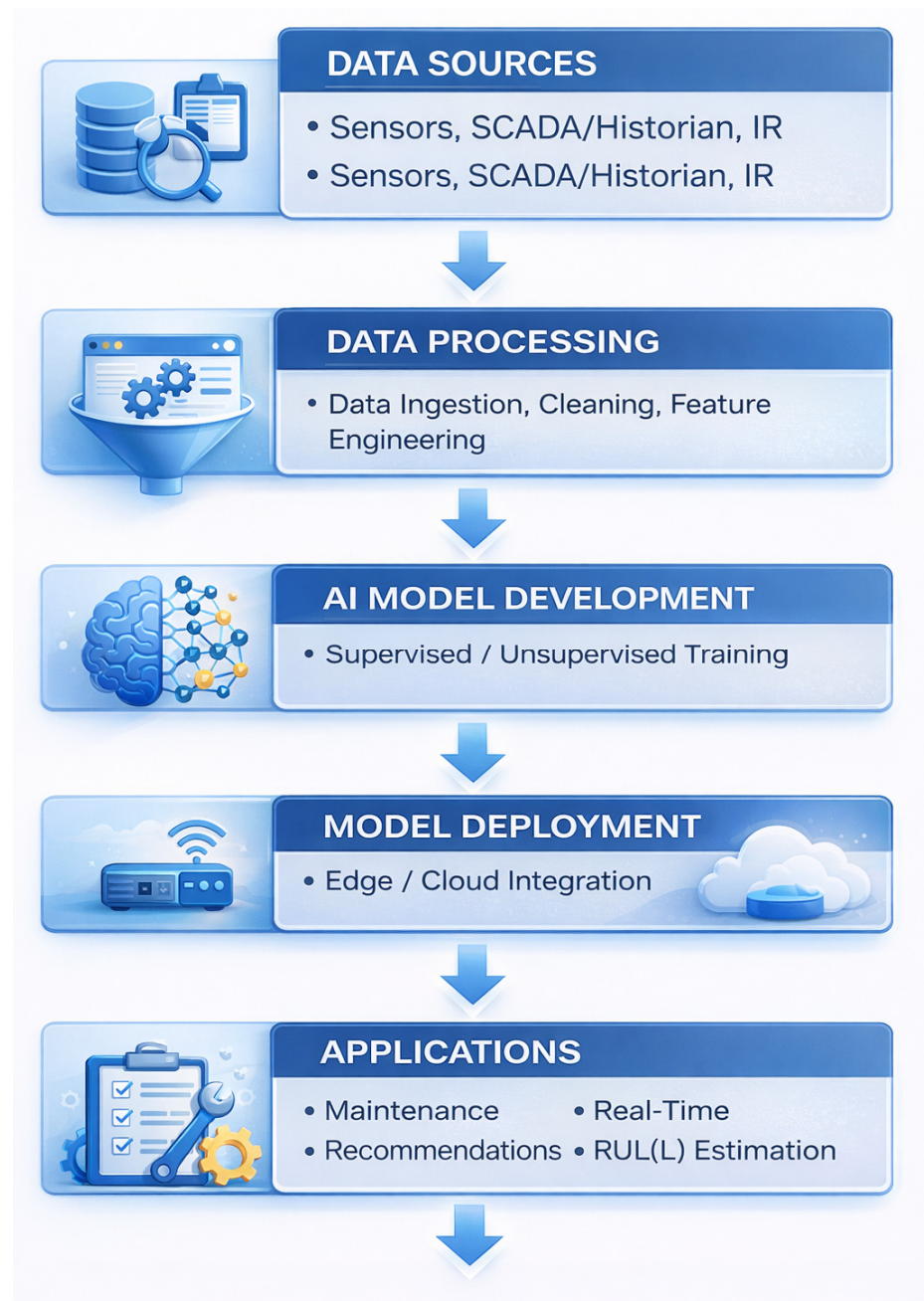


Figure 9. AI/ML pipeline for predictive maintenance and operational optimization in marine environments.

4.3. Autonomous Navigation and Intelligent Control Systems

Autonomous ships represent a paradigm shift in maritime transportation. AI techniques such as Bayesian networks, deep reinforcement learning and sensor fusion are central to autonomous navigation, collision avoidance and decision-making under uncertainty (Figure 10).

Feng Xiao and Jianjun Hu [24] proposed Bayesian network-based navigation systems able to handle uncertain maritime environments and complying with COLREGs. These systems show promising results in simulation environments, although real-world deployment is still limited by regulatory and safety concerns.

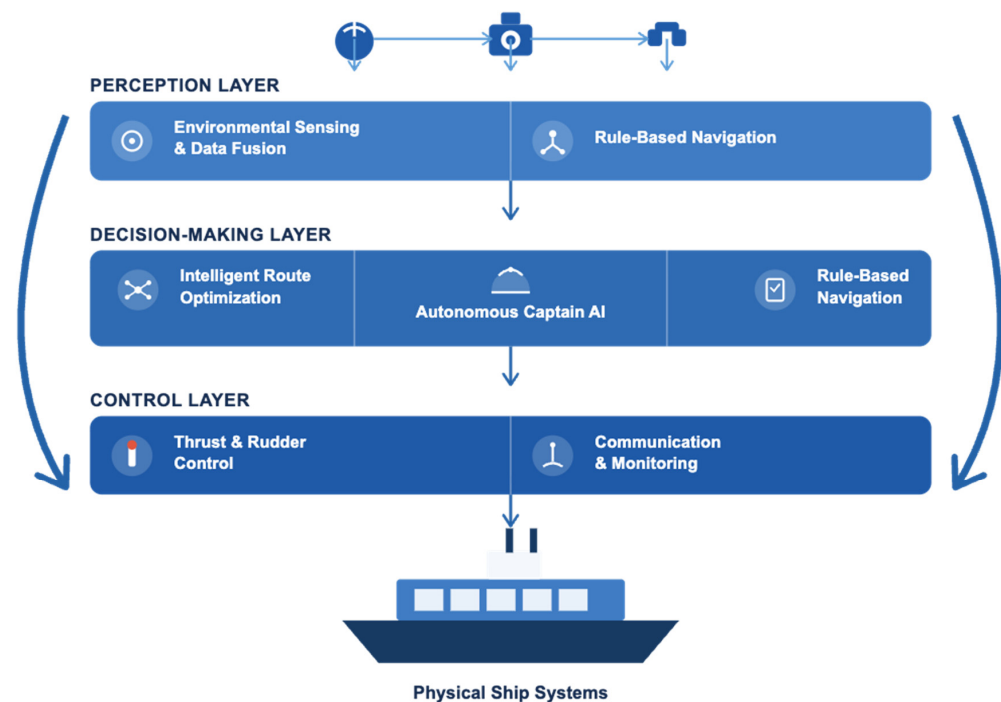


Figure 10. Autonomous ship navigation framework integrating perception, decision-making and control layers.

4.4. AI in Shipbuilding and Smart Shipyards

AI applications extend beyond ship operation to shipbuilding processes. Intelligent shipyards leverage AI for production planning, quality control, robotic welding and logistics optimization.

Swanljung demonstrated in [25] the feasibility of AI-based automation systems in shipyards, improving production efficiency and reducing human error. Vision-based inspection systems using deep learning are increasingly used for weld quality assessment and surface defect detection.

An specific industrial precedent for sensor-driven pipe management can be found in Fraga-Lamas et al. [26], who describe a Smart Pipe System deployed as part of Navantia's transition to a Shipyard 4.0. Framed around the vertical integration of production systems and the re-engineering of the ship life cycle, the system treats the large and varied population of pipes on board as a prospective cyber-physical monitoring target, tracked throughout fabrication and installation.

4.5. AI in Ship Design

AI can be deployed in ship design in many stages. Appropriate decisions during the execution of the ship design, accessing to rules, guidelines, best practices, lessons learned, etc., can be automated in different areas of application.

In the marine and maritime sector, penetration of AI has been clearly lower compared to other sectors. In both the design, manufacturing and operation phases of ships, there has been limited exploration of the possibilities offered by AI. Thus, an opportunity arises to upgrade and transform the shipbuilding and shipping industries into modern and forward-thinking industries.

As shipbuilding projects become increasingly complex, as shown in Figure 11, so does the desirability of having effective AI tools during the design phase.

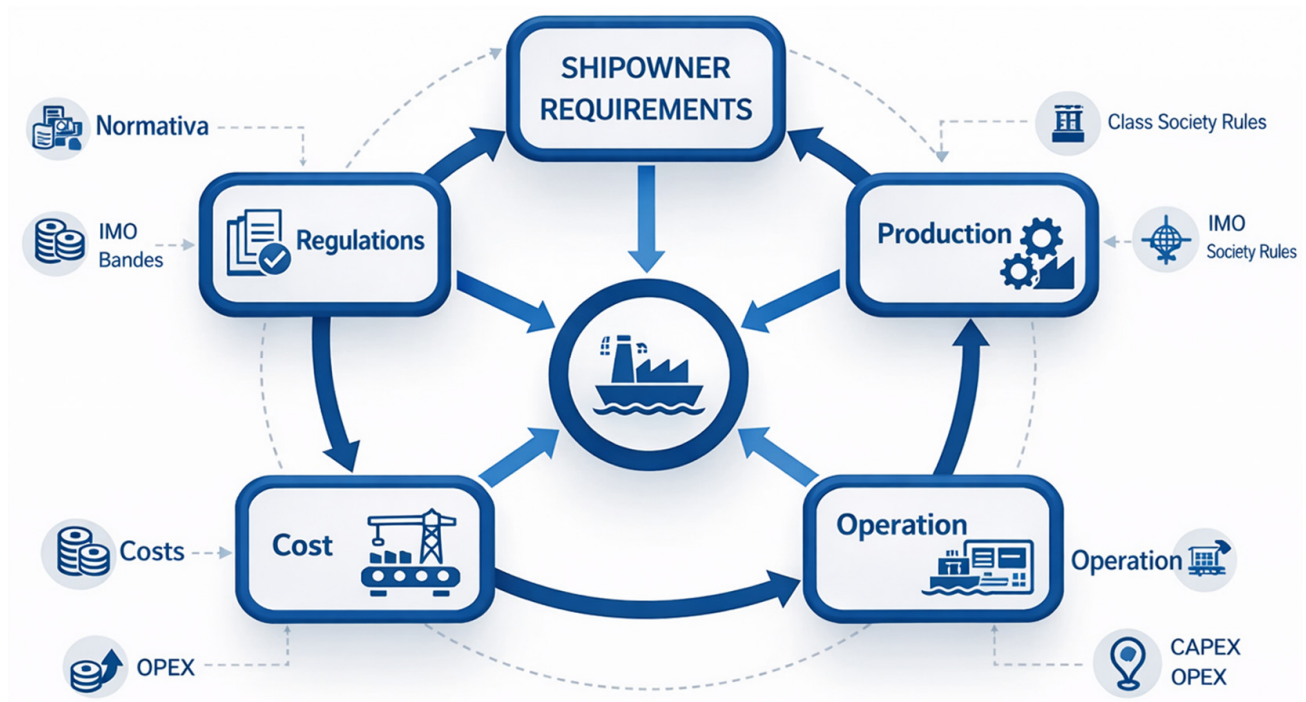


Figure 11. Complexity model in modern ship design. Multi-constraint network diagram.

Considering that 3D CAD systems are widely used nowadays, AI capabilities will need to be integrated into them. Having the FORAN[®] V80 system as a reference, the following benefits are considered:

- **Efficiency:** Efficient management of design options is achieved by consulting user manuals, design guidelines, calculation standards, etc., that the designer can have, with the help of AI, in interactive mode.
- **Reliability:** AI can incorporate algorithms that verify compliance with certain KPI's and make designers' tasks more precise.
- **Experience:** AI can help provide designers with comparative and historical data, insights from past projects, or lessons learned; all with the goal of helping to facilitate prototyping of new projects and identifying the best alternative.
- **Optimization:** Through AI, engineers can get online recommendations to adopt best practices and automate certain design tasks.

Additionally, the AI integrated into design systems can enrich the current project with data from various projects, making it a self-learning project.

Existing works typically focus on isolated algorithmic advances (e.g., routing optimization or document-centric AI, but rarely specify how regulatory corpora, hybrid reasoning and CAD interaction are integrated end-to-end. Figure 12 operationalizes this gap into an implementable architecture that can be reproduced across use cases and CAD platforms.

IBM Watson[®] is a suite of AI and ML tools and services that can be used for a range of applications.

When working with CAD FORAN[®] V80, the user can launch the module FORAN Cognitive[®] to receive AI assistance from Watson[®] on the desired topic. In this case, the AI engine returns a response based on the type of query made, the historical data, the user's profile and the Corpus (see in Figure 13) created for the FORAN Cognitive[®].

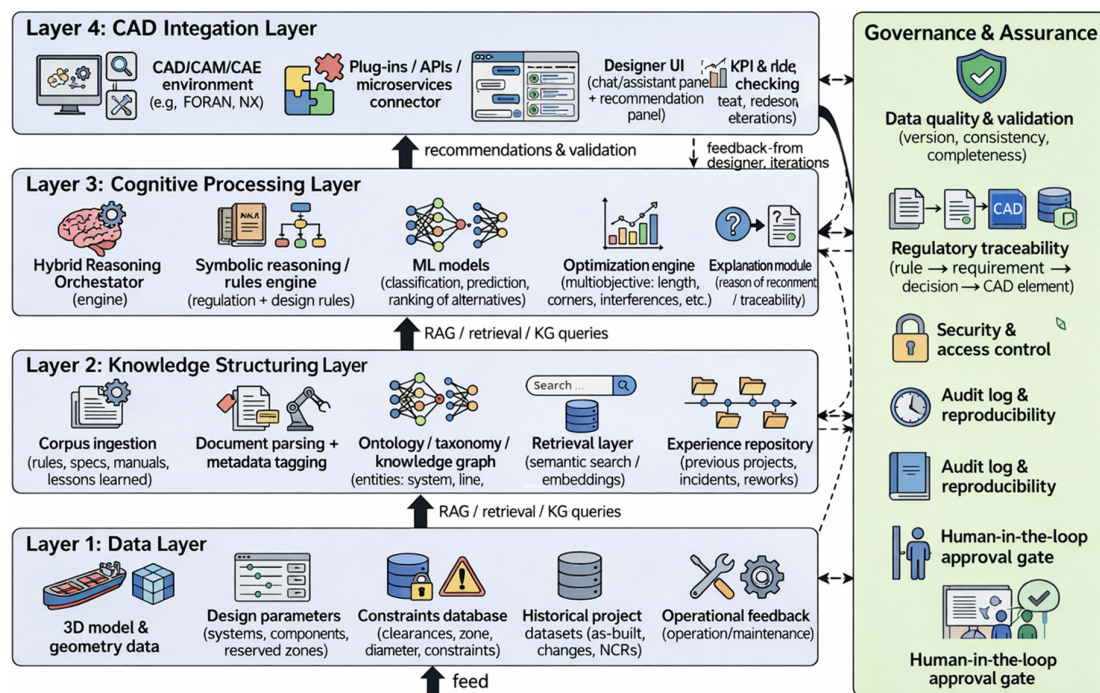


Figure 12. Governance-aware layered architecture for cognitive AI integration in marine CAD environments, illustrating the interaction between data sources, hybrid AI reasoning modules, regulatory knowledge corpora and the human-in-the-loop validation process.

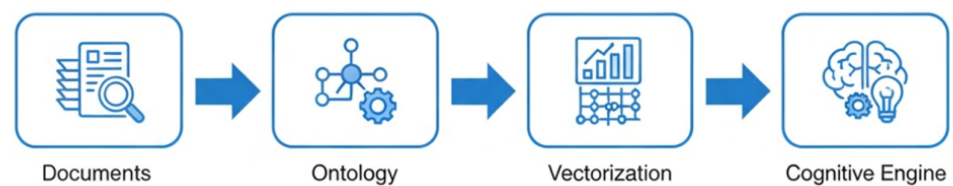


Figure 13. Engineering corpus-structured model. Transforming unstructured data into actionable knowledge.

A corpus is the set of information, data or rules related to a specific topic. It may be composed of, among other types of information, the rules of a classification society, rules of the national authority, rules of the shipyard or the designer's own rules based on his experience. The data included in the Corpus come from different sources:

- Common: Data of general application for each project, such as a standard for designs (for example, regulations of classification societies or equipment information provided by suppliers). Could be composed of data from third-party companies (suppliers, standardization organizations, Classification Societies. . .).
- Specific: Mainly related to data belonging to the know-how of each company, which is different (in many cases even contradictory) to the same data from another company (i.e., design guidelines or manufacturing procedures). Must be created internally by the company that uses the data.

The proposed methodology is structured as a layered architecture that integrates knowledge representation, AI reasoning and CAD interaction in a unified workflow.

As example, Corpus rules could be composed by:

- Design and manufacturing requirements.
- Design rules.
- Classification societies and national authorities.
- Regulations.

- Best practices.
- Technical specifications.
- Provider information.
- Relevant data from previous inherited projects.
- Guidelines and User manuals.
- Learned lessons.
- Operational data.

While IBM Watson® may not directly provide tools specifically for piping design, it can potentially be used in conjunction with other engineering software and tools to enhance certain aspects of the piping design process (Figure 14).

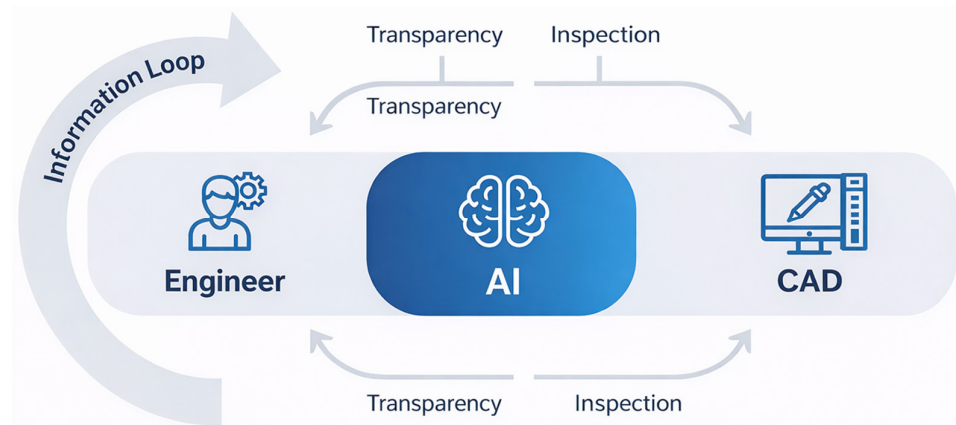


Figure 14. Human-in-the-loop validation process. Iterative refining and collaborative decision making.

A human-in-the-loop approach is incorporated to ensure traceability, explainability and alignment with engineering decision-making practices.

Here are some ways in which IBM Watson® integrated into FORAN® could potentially be used in piping design:

- **Data Analysis and Prediction:** IBM Watson's® machine learning capabilities can be used to analyze large amounts of data related to fluid flow, pressure, temperature and other parameters in a piping system. By analyzing this data, Watson® can provide insights and predictions on potential issues, such as flow restrictions, pressure drops, or temperature variations, which can help in optimizing the design and performance of the piping system.
- **Simulation and Optimization:** IBM Watson® can potentially be used in conjunction with CFD software to simulate fluid flow and optimize the design of piping systems. Watson® can analyze the CFD results and provide recommendations for design modifications to improve the efficiency and effectiveness of the piping system.
- **Collaborative Design:** IBM Watson® gives collaboration tools that can be used to facilitate communication and collaboration among team members involved in piping design. This can help in streamlining the design process, reducing errors and ensuring that all stakeholders are aligned throughout the design process.
- **Knowledge Management:** IBM Watson's® NLP capabilities can be used to capture and manage engineering knowledge related to piping design. This can include documentation, standards, best practices and other design guidelines. Watson® can also assist in retrieving relevant information during the design process, helping engineers make informed decisions.
- **Virtual Assistance:** IBM Watson's® conversational AI capabilities can be used to create virtual assistants that can provide interactive guidance and support to engineers

during the piping design process. This can include answering design-related questions, giving recommendations and assisting with design calculations.

4.6. Methodological Workflow for Cognitive AI Integration in Marine CAD Environment

To ensure reliability and regulatory compliance, the proposed framework adopts a human-in-the-loop iterative cycle. Rather than replacing the marine engineer, the system augments decision-making by giving contextualized recommendations derived from structured corpora and hybrid AI reasoning.

The cycle begins with the definition of engineering intent (e.g., routing a pipe segment under multi-constraint conditions). Context is assembled from the structured corpus through semantic retrieval mechanisms. Hybrid reasoning modules generate ranked alternatives, which are presented in the CAD interface together with explanatory metadata and constraint references (Figure 15).

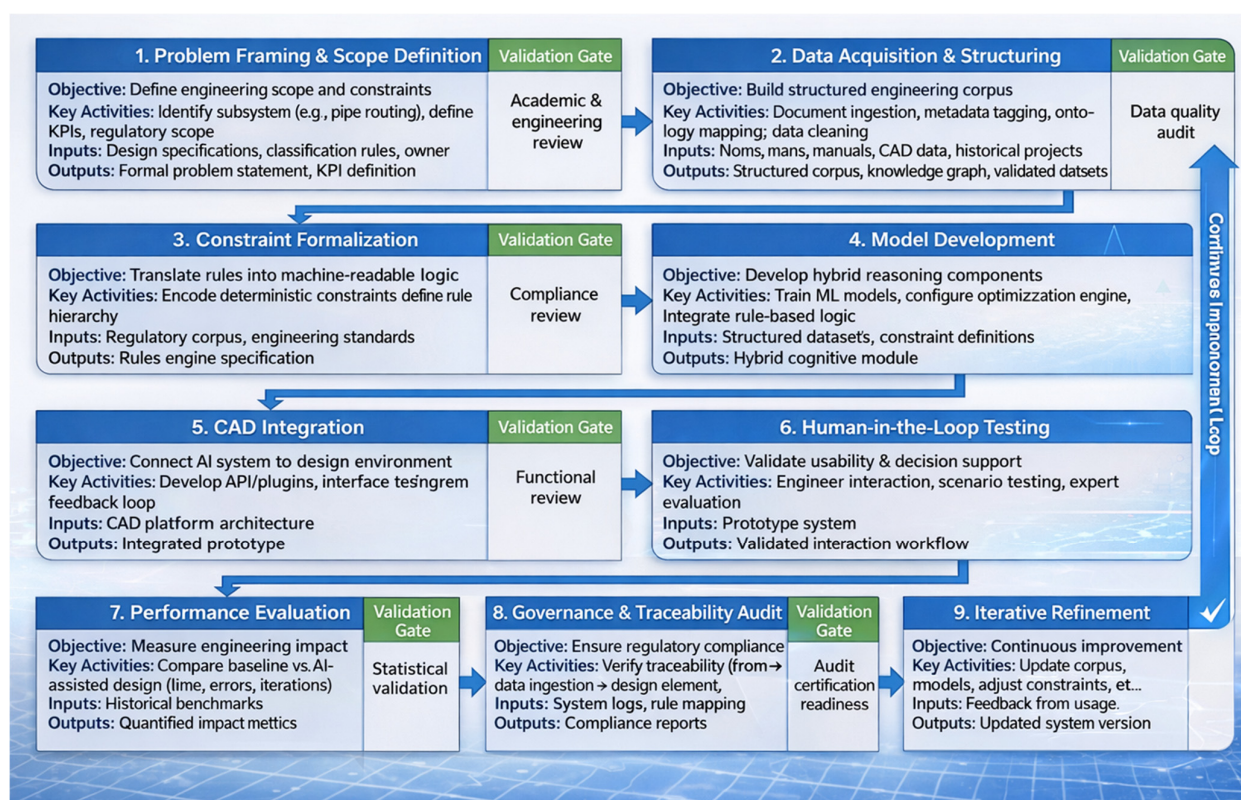


Figure 15. Methodological workflow for cognitive AI integration in marine CAD environments.

The engineer evaluates and adjusts the proposal, triggering feedback capture those updates model parameters, rule confidence weights, or knowledge graph linkages. This iterative process ensures continuous refinement while preserving accountability and decision authority in the engineering team.

Evidence for the value of interactive, feedback-driven design also comes from outside the marine sector. Brown [27] ran a controlled study in which participants used an interactive conceptual building design environment offering live feedback from surrogate models of structural and energy performance. Designers who worked with performance feedback tended to produce better-performing solutions and preferred environments combining feedback with continued flexibility, without any measurable reduction in the diversity of solutions explored.

The inclusion of transparency, traceability and compliance boundaries distinguishes the framework from autonomous AI approaches and aligns it with regulated marine engineering environments.

4.7. Implementation in Marine CAD Platforms

The proposed framework is designed to be integrated in existing marine CAD/CAM/CAE environments commonly used in shipbuilding, such as FORAN[®], AVEVA Marine, or Siemens NX. The implementation follows a modular architecture in which the cognitive AI components operate as external services connected to the CAD system through application programming interfaces (APIs).

The integration workflow can be summarized in the following stages:

- Data extraction from the CAD model, including geometric information, system topology and spatial constraints.
- Semantic enrichment of the design data through the engineering corpus, which includes classification society rules, design guidelines and historical project data.
- Execution of hybrid AI modules bringing rule-based reasoning and machine learning prediction together, with multi-objective optimization algorithms.
- Generation of ranked design alternatives presented to the designer in the CAD interface.
- Human validation and feedback incorporation, which allows for the continuous improvement of the AI models.

This architecture allows the AI system to operate as an intelligent decision-support layer rather than replacing the CAD environment itself. The approach ensures compatibility with existing industrial workflows while maintaining traceability and regulatory compliance.

5. Case Study: Automatic Pipe Routing

The pipe routing use case is intended as a representative validation scenario for the proposed framework rather than as a solution to ship design. It has been selected due to its multidisciplinary nature, combining spatial constraints, regulatory requirements, engineering rules and iterative decision-making in a CAD environment.

The objective of the case study is not to provide a complete solution to pipe routing, but to demonstrate the applicability of the proposed framework in a representative high-constraint engineering scenario.

The results should be expressed in normalized terms to allow comparison with reported performance improvements in similar AI-assisted engineering workflows.

The proposed framework contributes to bridging the gap between algorithm-centric AI research and its practical use in engineering environments. By integrating knowledge representation, reasoning mechanisms and CAD interaction in a governance-led structure, it tackles key limitations identified in the current literature.

5.1. Illustrative Design Scenario: A Conceptual Routing Corridor

To make the operation of the framework concrete, this subsection walks through a single illustrative routing task rather than a complete ship design. The scenario described below is hypothetical: it is used only to demonstrate how the architecture presented in Section 4 would be exercised in practice, and it does not rely on any CAD model, sensor data or shipyard record.

The scenario considers a seawater cooling line that must be routed from a pump located in the engine room to a heat exchanger positioned two decks above through a technical corridor shared with electrical trunking, ventilation ducting and structural stiffeners. This task is representative of the class of problems the framework targets because it combines hard geometric constraints, regulatory requirements, soft engineering preferences and the

need for a human designer to approve the final routing before release to detailed design. The constraint set assumed for the scenario is summarized below:

- **Functional requirement:** Connect two fixed points with a nominal DN80 seawater line while maintaining the required flow velocity and minimizing pressure loss.
- **Geometric constraints:** Minimum bend radius, deck penetration locations, corridor cross-section and clearance from structural stiffeners and other outfitting.
- **Regulatory constraints:** Minimum separation distances from electrical cabling and other systems, fire zone boundaries and insulation requirements derived from classification society rules.
- **Engineering preferences:** Minimizing the number of elbows and total length, reusing previously validated corridor segments, and avoiding single points of failure shared with other critical systems.

These four constraint families were selected because they mirror the categories already introduced in the corpus description in Section 4.5 (common rules, company-specific know-how, regulatory requirements and lessons learned), allowing the scenario to be traced directly back to the architecture rather than treated as a separate example.

5.2. Conceptual Walkthrough of the Framework Pipeline Applied to the Scenario

Applying the methodological workflow described in Section 4.6 and illustrated in Figures 12 and 15 to the scenario above produces the following conceptual sequence of steps. Each step is described at the level of what the framework would do and what information would be exchanged; no implementation was executed and no output was generated computationally.

- **Problem framing:** The designer specifies the routing intent (start point, end point, fluid service and nominal diameter) directly in the CAD interface. This intent is the trigger that instantiates the pipeline described in Section 4.6.
- **Corpus retrieval:** The system queries the structured engineering corpus for the rules relevant to the specific corridor and system type, such as classification society clearance requirements, shipyard-specific design guidelines for cooling systems and lessons learned tagged to similar corridors in past projects. Retrieval returns a constraint set comparable to the one listed in Section 5.1, expressed in a form the reasoning layer can consume.
- **Hybrid reasoning:** A constraint-satisfaction or graph-search component, analogous to the graph-based and reinforcement-learning approaches discussed later in this section, proposes a small number of candidate corridors that satisfy the hard geometric and regulatory constraints. A learned or heuristic scoring function ranks these candidates against the soft preferences, such as elbow count, length and reuse of validated segments.
- **Candidate generation:** The ranked alternatives are returned to the CAD interface together with the constraint references that justify each one, so the designer can see why a given route was proposed rather than receiving an unexplained geometric result.
- **Human validation:** The designer reviews the ranked alternatives, accepts, rejects or manually adjusts the proposed routing, and records the reason for any override. This is where the accountability boundary described in Section 3 is exercised in practice.
- **Feedback capture:** The accepted routing, together with the designer's adjustments, is fed back into the corpus as a new lessons-learned entry, closing the loop described in Figure 15 and making the segment available for reuse in future routing tasks.

It is important to state plainly what this walkthrough is and is not. It is a structured description of how the proposed architecture would be exercised on a single, representative

routing decision, intended to make the pipeline of Section 4 tangible. It is not an executed experiment: no CAD model was built, no reasoning module was implemented and no routing was actually generated or measured. The performance ranges discussed in the remainder of this section are drawn from comparable published studies on automated routing and design-automation workflows, not from this scenario, and should not be read as results obtained by running the framework.

The methodology evaluates the potential performance improvements using normalized engineering indicators, including reduction in design iteration cycles, decrease in routing conflicts and improved compliance verification with design rules and classification standards. Based on preliminary evaluations and comparable studies in automated routing systems, AI-assisted routing workflows may reduce design iteration time by approximately 20–40% while clearly decreasing late-stage interference corrections during detailed design.

These indicators provide a quantitative perspective on the potential efficiency gains achievable through cognitive AI integration in ship design environments.

5.3. AI Techniques Considered for Automating the Routing Pipeline

The reasoning and candidate-generation stages outlined above can draw on a range of AI techniques reported in the pipe-routing and CAD-automation literature. The remainder of this section surveys these techniques at a conceptual level, indicating where each would plug into the pipeline rather than presenting them as already implemented.

Piping design is a specialized engineering discipline that involves designing and configuring the layout of pipes, valves, fittings and other components for the transportation of fluids.

Pipe (and, by extension, distributor) layout is one of the most time-consuming engineering activities and is sensitive to physical and regulatory constraints. Historically, approaches based on the optimization of discretized networks/spaces integrated into CAD have been proposed, demonstrating that the problem can be formalized with graphs and designer preference parameters.

In recent years, advances have been observed in multi-objective models that incorporate more realistic sub-objectives (length, number of elbows, energy, air pockets, bend distance violations, etc.) and interface/diameter requirements, more closely approximating real-world design conditions. Studies are being published focusing on optimizing layout in specific contexts (e.g., engine rooms), highlighting the implications for cost and production schedule.

Within the specific domain of ship pipe routing, Dong et al. [19] proposed an improved multi-objective ant colony optimization algorithm that explicitly models ant moving direction, heuristic information and pheromone update rules to capture routing objectives and constraints. By integrating fast non-dominated sorting and non-dominated merging strategies, the method generates a Pareto set of routing alternatives that balance competing sub-objectives such as pipe length, number of elbows and clearance, rather than converging on a single optimum.

One of the most complex aspects of ship's equipment design, as well as the most time-consuming for designers, is the routing of piping on board. Because of this, pipe routing is one of the paradigmatic cases where the application of AI can help designers enhance the efficiency and accuracy of piping design and make the design itself more consistent and efficient.

AI can be applied in several ways in piping design:

- **Automated Routing:** AI algorithms can analyze various parameters such as fluid flow rates, pressure, temperature and other design requirements to automatically route pipes in the most optimal way. The application of AI techniques would help the

designer to make decisions and adopt routes that optimize and minimize the design, construction and assembly time without affecting the efficiency of the installation itself. This can help reduce design time and minimize the risk of errors in complex piping systems.

- **Clash Detection:** AI can be used to minimize interferences in complex pipe designs by using advanced machine learning algorithms to identify patterns in the design that could lead to interferences. This can be done by training a model to recognize different interference patterns and then applying it to the design. Additionally, AI can be used to build models that can predict possible interferences in the design based on different parameters such as pipe size, flow rate, pressure, valves position, etc. These models can then be used to optimize the design and reduce the risk of interferences. This can prevent costly rework during the construction phase.
- **Material Selection:** AI can analyze different materials and their properties, considering factors such as pressure, temperature, corrosion resistance and cost, to recommend the most suitable materials for specific piping applications. This can help optimize material selection and reduce the risk of material failures.
- **Predictive Maintenance:** AI can analyze sensor data from piping systems to predict and prevent potential failures, such as leaks or ruptures, by detecting anomalies in interactive. This can help improve the reliability and safety of piping systems, reducing downtime and maintenance costs.
- **Optimization of Pipe Sizing:** AI can analyze various factors such as flow rates, pressure drops and pipe material properties to optimize the sizing of pipes in a piping system. This can help ensure efficient and cost-effective piping designs that meet the required performance criteria.
- **Design Optimization:** AI can use machine learning algorithms to analyze vast amounts of data from past piping projects, including design parameters, performance data and feedback from operational systems, to optimize piping designs based on real-world performance. This can help improve design accuracy and efficiency over time.
- **Expert System for Design Rules:** AI can develop expert systems that capture the knowledge and experience of piping design experts, which allows for automated decision-making based on established design rules and best practices. This can help ensure consistent and compliant designs.

The following aspects are considered suitable for optimization and automation:

- Prioritizing systems.
- Selecting the main route areas (reservation of space).
- Selecting technological attributes of elements.
- Optimizing routing geometrically and operationally.
- Improving the results of previous projects.
- Considering the impact on production.
- Providing feedback on new designs with data from actual ship operations.

AI-based algorithms can also be used to generate virtual simulations of complex pipe systems to further optimize the design and allow for proactive preventative measures to be taken.

The design of a pipe system (as shown in Figure 16) to avoid interferences can be done using machine learning. Machine learning algorithms can be used to analyze the existing pipe system and identify features such as the number of pipes, the shape, the material, the size, etc.

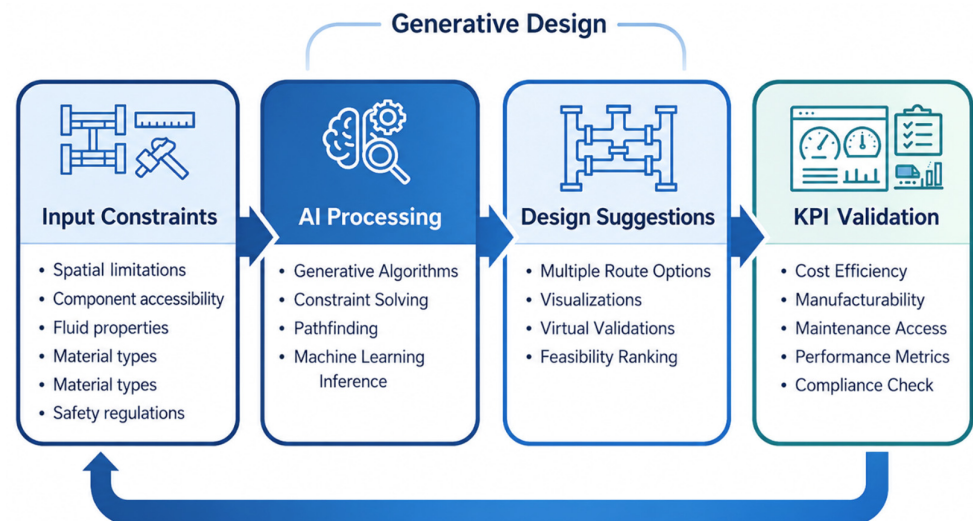


Figure 16. Application to pipe routing. Conceptual flow. Automatic pipe network design from requirements to performance metrics.

Using these features, the machine learning algorithm can be used to identify patterns and identify areas where interferences might occur. The machine learning algorithm can then generate a design that optimizes the pipe system to avoid these interferences. This design can then be tested and adjusted as needed to ensure that the pipe system does not cause any interferences.

There are a few different ways to avoid pipe interferences in machine learning algorithms. One way is to use different algorithms for different problems. For example, it could be used a machine learning algorithm to classify objects, and another to predict how a particular object will behave in the future.

Another way to avoid pipe interferences is to use a different data representations for each problem. For example, you might use a matrix representation for machine learning problems, and a vector representation for the problem of predicting how a particular object will behave in the future.

Machine learning can be used by using supervised learning algorithms such as:

- **Decision Trees:** Decision Trees can be used to identify the most appropriate routes for pipes to take in order to avoid interferences.
- **Support Vector Machines:** Support Vector Machines can be used to identify the most efficient ways to route pipes and to determine the best locations for pipe connections.
- **Artificial Neural Networks:** Artificial Neural Networks can be used to identify and recognize potential interferences between pipes, as well as to determine the most optimal route for pipes [14].
- **Reinforcement Learning:** Reinforcement Learning can be used to identify the most efficient routes for pipes and to optimize the design of the ship's piping system.
- **Genetic Algorithms:** Genetic algorithms can be used to optimize designs for avoiding pipe interference by selecting the most suitable designs from a population of potential solutions based on a set of criteria. First, a population of initial designs is created, each of which has different characteristics with respect to the criteria such as pipe sizes, pipe locations and pipe shapes. Then, the fitness of each design is evaluated according to the criteria. Finally, the designs with the highest fitness values are selected and used as parents to create new designs, through crossover, mutation and other genetic operations. The new designs are then evaluated and added to the population. This process is repeated until the desired solution is found.

These algorithms can be instructed and trained to recognize blueprints in the data that specify probable interferences and can then be used to predict and avoid pipe interferences.

Additionally, unsupervised learning algorithms such as clustering and anomaly detection can be used to identify unexpected changes in the data that may be used to detect anomalies in the design of the pipeline, such as incorrect distances between components, which could lead to interference.

Finally, reinforcement learning techniques can be used to teach a system and optimize the design of the pipeline. It could be done by taking a series of actions based on the data it receives and finding the most efficient route to avoiding potential conflicts.

Software can be used to automatically detect and classify the different types of pipe interferences that can be found in a piping system.

The use of AI in piping design can greatly enhance the efficiency, accuracy and safety of piping systems by automating repetitive tasks, optimizing designs, detecting clashes, predicting failures and leveraging data-driven insights. However, it is important to note that AI is not a replacement for human expertise and judgment, but rather a tool that can augment the capabilities of piping designers and engineers.

Taken together, Sections 5.1–5.3 show how the governance-aware architecture of Section 4 could, in principle, be exercised on a representative routing task. This case study remains a conceptual illustration: the constraint set, the pipeline walkthrough and the candidate AI techniques are presented to demonstrate the feasibility of the architecture, not to report measured design outcomes. Empirical validation on real CAD models and shipyard data is identified as a priority for future work in Section 6.

5.4. Illustrative Comparison: Conventional Versus Framework-Assisted Workflow

To make the expected impact of the framework tangible before any real deployment, this subsection narrates, step by step, how the routing corridor introduced in Section 5.1 would likely unfold under a conventional manual workflow, and contrasts it with the framework-assisted pipeline described in Section 5.2. The comparison is qualitative and illustrative: it describes the mechanism by which time savings are expected to arise, not a measurement taken from a fielded project.

Conventional workflow. In a typical manual process, the designer routes the corridor based on experience and static reference documents, checking classification society clearance rules, electrical separation requirements and structural drawings manually and largely sequentially. Coordination with the electrical and structural disciplines happens through review meetings or document exchange rather than a shared, queryable constraint set, so conflicts with other systems are often not visible until a structural or electrical designer reviews the routing independently. Because of this, a meaningful share of clashes and non-conformances tend to surface late, during detailed design or even construction, at which point correcting them requires rework that is more costly than an equivalent change made earlier.

Framework-assisted workflow. Under the pipeline described in Section 5.2, the same corridor task begins with corpus retrieval, which surfaces the relevant classification, electrical-separation and structural constraints before any candidate route is proposed rather than after. Hybrid reasoning generates a small set of candidates that already satisfy these constraints, and the CAD interface presents them together with the reasons each was proposed, so cross-discipline conflicts that would otherwise be found later, by a different reviewer, are instead surfaced at candidate-generation time. The designer still makes the final call, but the review is against pre-checked options rather than a single unchecked proposal.

The mechanism this comparison points to is a shift in when conflicts are detected, from late in the process (detailed design or construction, under the conventional workflow) to early in the process (candidate generation, under the framework-assisted workflow). This shift is the basis for the expectation, discussed in Section 5, that design iteration time and late-stage rework could be reduced, and it is directionally consistent with the ranges reported in comparable published studies on automated routing and design-automation workflows cited earlier in this section.

This comparison remains a narrative illustration of an expected mechanism, not a timed trial: no shipyard measured either workflow for this task, and no design-time figures were collected. Turning this expectation into evidence requires the industrial validation study suggested in Section 6: Proposed Industrial Validation Plan.

Taken together, Sections 5.1–5.4 show how the governance-aware architecture of Section 4 could, in principle, be exercised on a representative routing task. This case study remains a conceptual illustration: the constraint set, the pipeline walkthrough and the candidate AI techniques are presented to demonstrate the feasibility of the architecture, not to report measured design outcomes. Empirical validation on real CAD models and shipyard data is identified as a priority for future work in Section 6.

6. Challenges and Future Research Directions

Despite the substantial progress achieved in applying AI to ship design and marine engineering, several challenges continue to hinder its full-scale adoption. Addressing these challenges is crucial for the development of safe and widely accepted AI systems in maritime applications.

One of the most significant obstacles is the scarcity of standardized, high-quality datasets. Ship design and operational data are often fragmented across different organizations, proprietary CAD platforms, or sensitive operational logs, limiting the ability to train generalizable AI models. In addition, data heterogeneity, arising from differences in vessel types, design standards and sensor systems, poses additional challenges for model interoperability. Future research must focus on establishing common data standards, promoting secure data-sharing mechanisms and creating annotated datasets that capture the diversity of marine engineering environments. The development of synthetic data generation techniques, including simulation-based datasets and physics-informed synthetic models, may also provide a viable pathway to supplement real-world data.

AI models, particularly deep learning networks and complex optimization algorithms, often operate as black boxes, giving limited insight into their internal decision-making processes. In maritime contexts, where safety and compliance are paramount, the lack of transparency can impede trust and adoption. Explainable AI methods must be further developed to ensure that model predictions and recommendations can be interpreted, audited and validated by designers, engineers and regulatory authorities. Techniques such as model-agnostic explanations, attention mechanisms and hybrid symbolic-learning approaches hold promise for bridging the gap between AI autonomy and human interpretability. Research should also investigate frameworks for integrating human-in-the-loop verification to allow domain experts to oversee, correct, or refine AI-driven design decisions.

AI systems must operate in alignment with maritime regulations, including International Maritime Organization (IMO) conventions and classification society rules [28]. Currently, regulatory guidance on AI implementation in ship design, navigation [29] and operation is still evolving, leading to uncertainty regarding compliance and certification. Future research should focus on developing AI evaluation frameworks that embed regulatory requirements directly into the design and validation process. This includes traceability mechanisms, standardized assessment protocols and formal verification of

AI-driven decisions to ensure adherence to safety, operational and environmental standards. Collaborative efforts between academia, industry and regulatory bodies will be essential to define practical guidelines and accelerate regulatory acceptance.

Purely data-driven AI models are often limited by the availability of large datasets and may fail to generalize under scenarios not represented in the training data. Hybrid modeling approaches, such as PINNs and surrogate models that integrate first-principles knowledge, offer a promising pathway to bridge the gap between physics-based and data-driven methodologies. Future research should investigate how hybrid approaches can enhance predictive accuracy, reduce data dependency and improve interpretability, particularly in applications like fluid dynamics simulations, structural integrity analysis [10] and pipe routing optimization. These methods can also facilitate uncertainty quantification, allowing designers to make risk-informed decisions with higher confidence.

To fully exploit the potential of AI in marine CAD and ship design, future research should prioritize the following areas:

- **Standardized, high-quality datasets:** Initiatives to create shared, annotated datasets for ship design, operational monitoring and system performance will enable research and facilitate the benchmarking of AI methods.
- **Explainable and trustworthy AI:** The development of interpretable models and human-in-the-loop workflows will enhance safety, regulatory compliance and designer confidence.
- **Large-scale validation and deployment:** Field trials and operational validation in real shipyards and vessels are necessary to evaluate AI performance under real-world conditions and identify practical limitations.
- **Integration with digital twins and cognitive CAD systems:** Research should explore AI-augmented digital twins for predictive simulation, automated design iteration and intelligent decision support.
- **Multi-objective and multi-agent optimization frameworks:** Advanced optimization techniques can address the complexity of competing design objectives, such as cost, efficiency, safety and maintainability.
- **Regulatory-aware AI frameworks:** Embedding compliance checks and traceability mechanisms directly in AI models will facilitate adoption and certification in safety-maritime applications.

Proposed Industrial Validation Plan

The case study in Section 5 demonstrates the feasibility of the proposed architecture but does not measure its effect on real engineering design times, as stated throughout that section. Converting this conceptual illustration into evidence requires a real deployment, and this subsection outlines the pilot study design needed to obtain it.

- **Partner and scope:** One or more shipyards or engineering offices already operating a commercial marine CAD platform, such as those discussed in Section 4.7 (FORAN®, AVEVA Marine, or Siemens NX), selecting a bounded and repeatable task class, such as single-system corridor routing, so that complexity is comparable across trials.
- **Study design:** A matched before/after or parallel-team comparison, in which comparable routing tasks are completed conventionally by one team or project and with framework assistance by another, or by the same team across comparable projects, to reduce the influence of individual designer experience on the result.
- **Metrics:** Elapsed time from task assignment to designer-approved routing; the number of design iteration cycles; the number of clashes or non-conformances detected after approval, during detailed design or construction; rework hours attributable to late-stage corrections; and designer-reported trust and usability ratings.

- **Duration and sample size:** A pilot spanning a defined design phase or ship program, with enough comparable routing tasks to support a statistical comparison between workflows rather than a single anecdotal case.
- **Reporting:** Results expressed using the normalized indicators already defined in Section 5, enabling direct comparison with the illustrative ranges discussed there and with the published studies cited throughout this work, and reported regardless of outcome, including null or negative results, to avoid publication bias.

This plan has not yet been executed. It is proposed here as the immediate next step following this work, and as the mechanism by which the expectations discussed in Section 5.4 would be confirmed, revised or rejected against real engineering design-time data.

In summary, overcoming these challenges requires a multidisciplinary approach that combines AI expertise, naval architecture knowledge, regulatory understanding and human-centered design principles. By addressing data limitations, improving explainability, developing hybrid modeling approaches and validating AI in operational environments, future research can unlock the full potential of cognitive AI in ship design, as shown in Table 3, which allows for safer, more efficient and innovative maritime systems.

Table 3. Performance indicators for AI-assisted pipe routing.

Metric	Traditional CAD Workflow	AI-Assisted Workflow	Expected Improvement
Design iteration cycles	High	Reduced	20–40%
Clash detection stage	Late design	Early design	Reduced rework
Compliance verification	Manual	Semi-automated	Faster validation
Design time	High	Moderate	Improved productivity

7. Conclusions

Our contribution here is methodological rather than domain-exhaustive. It gives a structured and governance-led framework for integrating cognitive AI into marine CAD environments and shows, through a pipe routing use case, how such integration can be conceptualized in a high-constraint engineering context.

AI has demonstrated considerable potential in naval architecture and shipbuilding, giving innovative solutions to some of the most complex engineering challenges in the maritime sector. This review highlights that AI applications are reaching a notable level of maturity in areas such as hull form optimization [8], structural analysis and predictive maintenance [23], where machine learning, evolutionary algorithms and physics-informed models have enabled more efficient, accurate and data-driven design workflows. At the same time, rapidly evolving domains such as autonomous navigation, smart shipyards and interactive operational decision support are pushing the boundaries of what AI Donecan achieve, which allows for greater automation, risk mitigation and operational efficiency across the lifecycle of a vessel.

Despite these advances, several challenges remain. The integration of AI into marine CAD environments and ship operations requires high-quality, structured datasets, validation procedures and strict adherence to regulatory standards, such as those defined by classification societies and international maritime organizations. Issues related to explainability, trust and human–AI collaboration also demand careful attention, particularly in safety- contexts where decisions must be both reliable and interpretable. The adoption of AI is uneven across ship design and operational domains, with some sectors still relying heavily on traditional rule-based methods due to organizational inertia or concerns about liability and compliance.

Looking forward, the full potential of AI in the maritime sector will depend on sustained collaboration between academia, industry and regulatory bodies. Standardized frameworks for AI evaluation, lifecycle management and traceability are essential to ensure that cognitive and autonomous systems can be deployed safely, effectively and ethically. Hybrid approaches that combine physics-based knowledge with learning algorithms, as well as human-in-the-loop and explainable AI methods, are likely to play a central role in bridging current gaps between computational intelligence and domain expertise. Newer trends such as digital twins, multi-agent optimization and intelligent decision support platforms promise to transform ship design, construction and operations by which allows for interactive feedback, predictive insights and fully integrated workflows.

This work focuses on the definition of a methodological and architectural framework rather than on the development of a specific optimization algorithm. The objective is to provide a structured approach for integrating cognitive AI into marine CAD environments, which allows for future experimental implementations and industrial validation.

This paper puts forward a governance-led method for integrating cognitive AI into marine CAD environments. The contribution is primarily at the system and integration level, giving a structured basis for incorporating AI into engineering workflows under regulatory and operational constraints.

This work does not aim to provide a complete ship design solution, but rather a methodological and architectural contribution addressing a recognized gap in the integration of AI into marine CAD environments.

The conceptual pipe-routing use case shows the feasibility of the approach in a representative high-constraint design scenario. Future work will focus on empirical validation and industrial implementation.

The validation presented in this work is conceptual and scenario-based, rather than based on full-scale industrial implementation. However, the performance improvements estimated in this study are consistent with reported ranges in AI-assisted engineering workflows, particularly in routing optimization and design automation tasks, where reductions in iteration cycles and early conflict detection have been previously observed.

Therefore, the results should be interpreted as an initial validation of feasibility and consistency rather than as definitive quantitative performance metrics.

In conclusion, while AI has already proven its value in improving efficiency, reducing design iteration times and enhancing predictive capabilities, its continued success in naval architecture will require addressing data, regulatory and trust-related challenges. By fostering interdisciplinary research, developing methodological frameworks and prioritizing safe and transparent AI deployment, the maritime sector can harness the potential of AI to achieve smarter, safer and more sustainable ship design and operation.

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