AI-Based Optimization and Hydrodynamic Performance of Floating Pontoon Breakwaters through Experimental and Numerical Modeling

James RIFFAT(1), Seyed Reza SAMAEI(2), Mohammad Asadian GHAHFAROKHI(3)

(1) World Society of Sustainable Energy Technologies, Nottingham, NG11 6AA, United Kingdom, (2) Department of Marine industries, Science and Research Branch, Islamic Azad University, Tehran, Iran, (3) Department of Marine industries, Science and Research Branch, Islamic Azad University, Tehran, Iran

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Abstract: Ensuring effective coastal protection requires not only attenuating incoming wave energy but also preserving the operational reliability of marine infrastructure. This study investigates the hydrodynamic behavior of two pontoon-type floating breakwaters—simple and stepped—through a combined program of new laboratory wave-flume experiments and high-fidelity numerical modeling in ANSYS AQWA. A 1:15 physical model was constructed and tested under regular waves with incident heights of 2.2–3.3 cm and periods of 0.44–0.84 s. The experiments showed that the simple pontoon achieved optimum energy dissipation at shorter wave periods (0.44 s), whereas the stepped configuration performed more efficiently in longer waves (0.84 s). Transmission coefficients (K_t) ranged from 0.2 to 1.5, with the stepped design consistently exhibiting stronger wave-energy reduction. Numerical simulations reproduced the laboratory findings with a maximum deviation of about 8%. To further enhance performance, an artificial-intelligence framework was developed that integrates artificial neural networks (ANNs) for rapid prediction of wave-induced loads, genetic algorithms (GAs) for multi-objective structural optimization, and reinforcement learning (RL) for adaptive real-time control. Together these methods lowered the mean transmission coefficient from 0.52 to 0.40 and improved computational efficiency by 88%. In addition, a prototype digital-twin environment, linked to an IoT sensor network, was established to enable continuous structural monitoring and to support condition-based maintenance. The results highlight the dominant influence of breakwater geometry, draft, and mooring characteristics on hydrodynamic behavior and demonstrate that AI-guided optimization provides a practical, scalable, and cost-effective pathway for designing resilient and low-carbon coastal infrastructure.

Keywords: Floating Breakwaters, Coastal Engineering, AI Optimization, Digital Twin, Experimental Validation.

1 Introduction

Coastal erosion and wave-induced forces remain major engineering challenges, particularly in high-energy shorelines where ports, harbors, and related infrastructures are at risk. Breakwaters play a key role in dissipating and redirecting incident wave energy to maintain navigational safety and operational continuity. Traditional fixed breakwaters provide reliable attenuation but often involve high capital investment, long construction timelines, and sensitivity to geotechnical conditions. Floating breakwaters, on the other hand, offer flexibility, lower seabed disturbance, and cost-effective installation when properly configured in terms of draft, mass, and mooring stiffness. While the basic principles of floating breakwater design are well established, recent demands for sustainable and adaptive coastal protection—driven by climate change and the need for low-carbon infrastructure—require innovative design approaches that integrate advanced modelling and intelligent optimization. These needs form the context for the present study.

2 Literature Review

Early reviews established the fundamental understanding of floating breakwater behavior and highlighted their potential advantages over fixed structures (Hales, 1981). Subsequent experimental work demonstrated the effectiveness of pile-restrained systems in attenuating wave energy (Isaacson *et al.*, 1998) and clarified how geometric configuration influences reflection and transmission characteristics (Koutandos *et al.*, 2005). Complementary investigations explored innovative forms such as π-shaped layouts to improve energy dissipation efficiency (Gesraha, 2006). Further studies underlined the importance of mooring configuration. Liang *et al.* (2022) showed that mooring pretension operates as a primary tuning parameter controlling natural periods and overall hydrodynamic stability. Despite these advances, many designs continue to depend on empirical relations or isolated numerical simulations that are not fully embedded in modern optimization workflows. Where high-fidelity solvers like finite-element and computational fluid dynamics models are used, the need for heavy computational resources and complex parameter calibration limits broad parametric sweeps and rapid design iteration (Carraro *et al.*, 2022). Although genetic algorithms have been introduced to improve design optimization (Mao *et al.*, 2024), most applications remain focused on static geometric tuning and lack dynamic, adaptive control strategies.

Recent developments in artificial intelligence (AI) and machine learning (ML) offer a promising pathway beyond these constraints. Artificial neural networks (ANNs), genetic algorithms (GAs), and reinforcement learning (RL) have demonstrated strong potential for wave-energy forecasting, structural-response optimization, and autonomous control (Castiglioni *et al.*, 2021; Cravero *et al.*, 2023). Adjacent maritime applications reinforce this promise: predictive maintenance of ship machinery has reduced unplanned outages (Jimenez *et al.*, 2020), and autonomous surface vehicles now routinely employ deep-learning-based path planning under uncertain sea states (Tsai *et al.*, 2019; Qiao *et al.*, 2023). Despite this progress, the application of AI-driven methods to floating breakwater design and optimization remains limited. Most current

studies still treat draft, width, or mooring characteristics in isolation and rarely incorporate uncertainty quantification suitable for decision support. There is also a lack of integrated frameworks that combine physical experiments, numerical modeling, and AI-based adaptive optimization within a single design process.

Alongside hydrodynamic efficiency, environmental sustainability and life-cycle carbon accounting are becoming critical metrics for coastal and port infrastructure. Recent life-cycle studies emphasize the need to quantify both embodied and operational greenhouse-gas (GHG) emissions when assessing coastal defenses. A process-based life cycle assessment comparing grey levees, green–grey levee–oyster-reef systems, and a no-protection baseline showed that the green–grey option substantially reduces GHG emissions while maintaining comparable flood protection, underscoring the mitigation value of nature-inclusive defenses when materials and construction phases are fully considered (Hasan *et al.*, 2024). Broader system perspectives from port operations demonstrate that decarbonization pathways are highly sensitive to the electricity mix and power-supply scenarios, which implies that the life-cycle carbon of coastal protection for ports should be evaluated in conjunction with port-energy strategies (Issa-Zadeh *et al.*, 2024). At the intervention level, a life-cycle assessment of coastal enhanced weathering found that carbon-removal benefits are offset partly by supply-chain impacts—such as mining, comminution, and transport—highlighting the importance of clear system boundaries and uncertainty analysis when reporting net climate outcomes (Foteinis *et al.*, 2023). Complementary reviews of shoreline hardening show broad environmental externalities associated with revetments and seawalls throughout construction and use phases, reinforcing the case for low-carbon materials, optimized logistics, and hybrid green–grey designs in future coastal infrastructure (Sanitwong-Na-Ayutthaya *et al.*, 2023).

Given these gaps, the present research introduces a fully integrated experimental–numerical–AI framework for floating pontoon breakwaters. By combining physical wave-flume experiments, high-fidelity ansYS AQWA modeling, and AI-driven optimization (ANN, GA, and RL), this study aims to:

- overcome the computational cost and limited adaptability of conventional approaches,
- provide real-time and scalable design solutions for varying sea states,
- and incorporate environmental and economic sustainability considerations into breakwater design.

This combined methodology moves beyond prior work by enabling dynamic, data-driven optimization and by demonstrating practical applicability through a real-world case study at the Port of Rotterdam.

3 Objectives and Research Contributions

This research proposes an AI-driven optimisation framework for floating breakwaters that links experimental validation, numerical modelling, and real-time adaptive control. The objective is straightforward: strengthen wave attenuation while keeping computational cost low. Unlike prior studies that leaned on either tank tests or simula-

tion alone, the present approach integrates three complementary tools. Deep-learning surrogates provide fast hydrodynamic predictions, a genetic optimiser explores the design space, and a reinforcement-learning agent adjusts geometry, draft, and mooring settings as conditions evolve. In combination, configurations are refined dynamically rather than on fixed schedules, yielding improved performance with restrained computational demand. To complement the physical and numerical programmes, a data-driven layer is incorporated. Artificial neural networks predict wave-induced forces from incident spectral descriptors and geometry, with training and cross-validation carried out against both flume measurements and AQWA outputs to limit overfitting. Structural parameters are then selected *via* a multi-objective genetic algorithm that balances transmission, motions, and structural demand under explicit constraints on draft, freeboard, and mooring loads. A reinforcement-learning policy supplies closed-loop adaptation by updating draft and mooring pretension as sea states drift, replacing fixed settings with responsive control. Taken together, this sequencing of prediction, optimization, and control improves responsiveness while keeping computational expense within practical bounds. Linking a digital-twin model to an IoT sensor network supports condition-based maintenance and continuous audit of structural performance rather than episodic checks. The resulting evidence base offers practical guidance for coastal engineers, designers, and policymakers, and points to floating-breakwater solutions that are responsive to changing sea states, proportionate in life-cycle cost, and attentive to environmental constraints—qualities that matter for credible coastal-resilience planning.

4 Methodology

This study adopts an integrated methodology that combines physical experimentation, numerical analysis, and artificial intelligence–based optimization to evaluate the hydrodynamic performance of floating pontoon breakwaters. Laboratory wave-flume tests, conducted under controlled spectra and water depths, quantified transmission, energy dissipation, and salient structural responses. Complementary simulations in ANSYS AQWA modelled wave–structure interaction in detail, supported geometry tuning through targeted optimization, and were cross-checked against the flume records to substantiate the experimental findings. To improve design effectiveness and operational efficiency, three machine-learning components were added: an artificial neural network for predicting wave-induced forces, a genetic algorithm for structural parameter optimization, and a reinforcement-learning controller for adaptive operation under changing sea states. These additions reduced wave-transmission coefficients and shortened computation time while maintaining—often improving—predictive accuracy, indicating that intelligent optimization is a practical tool for modern coastal engineering.

This study applies an integrated, three-stage methodology that connects laboratory experiments, high-fidelity numerical modeling, and advanced AI-based optimization into one coherent framework. In the first stage, a 1:15 scale physical model of both simple and stepped pontoon breakwaters was tested in a controlled wave flume to measure key hydrodynamic responses such as transmission coefficients, energy dissipation, and structural stability. In the second stage, high-resolution simulations

were performed in ANSYS AQWA, where mesh sensitivity analysis and validation against experimental measurements ensured predictive accuracy and quantified numerical uncertainties. In the third stage, an artificial intelligence layer combined three complementary algorithms—artificial neural networks (ANNs) for rapid prediction of wave-induced forces, a multi-objective genetic algorithm (GA) for structural parameter optimization, and a reinforcement learning (RL) controller for real-time adjustment of draft and mooring tension—allowing the system to adapt dynamically to changing sea states. These three components are closely linked through a digital-twin environment that continuously integrates sensor data for condition-based monitoring and adaptive control. This integrated workflow enabled closed-loop interaction between physical measurements, numerical simulations, and intelligent optimization, leading to robust hydrodynamic performance, significant computational efficiency, and improved life-cycle economic and environmental outcomes.

4.1 Experimental Setup

4.1.1 Physical Modeling of Floating Breakwaters

A 1:15 scale physical model was designed, fabricated, and tested by the authors for two floating breakwater configurations: a simple pontoon and a stepped pontoon. All experiments were performed in a controlled laboratory wave flume to evaluate wave attenuation and structural response under North Sea–type conditions. The ranges of incident wave height (2.2–3.3 cm) and wave period (0.44–0.84 s) were selected to be representative of the Port of Rotterdam, using published metocean datasets and peer-reviewed analyses of North Sea conditions (e.g., Rutten *et al.*, 2024; Rijnsdorp *et al.*, 2021) to guide prototype equivalence. The models were built from 3 mm transparent plexiglass; laser-cut panels were solvent-bonded for watertightness and the joints sealed with aquarium-grade silicone to ensure durability over repeated runs. The flume measures 16 m × 0.50 m × 0.80 m and is equipped with a piston-type wavemaker capable of generating both regular (monochromatic) and irregular (spectral) seas. To minimize unwanted reflections, an absorbing sloped beach was installed at the downstream end. The breakwaters were restrained with pretensioned cable moorings arranged to limit surge, sway, and yaw, thereby reproducing full-scale hydrodynamic behavior with high fidelity. This dedicated laboratory program provided the complete experimental dataset used to calibrate and validate the subsequent high-fidelity numerical modeling in ANSYS AQWA and to train the artificial-intelligence optimization framework.

Table 1: Dimensional Specifications of the Floating Breakwater Models. Samaei *et al.* (2016)

Breakwater Type	**Length (m)**	**Width (m)**	**Height (m)**	**Scaled Length (cm)**	**Scaled Width (cm)**	**Scaled Height (cm)**
Simple Pontoon	19.9	4.0	1.8	48	27	16
Stepped Pontoon	20.3	4.5	2.2	50	30	18

4.1.2 Justification for the 1:15 Scale Model

A 1:15 scale was adopted in accordance with Froude similarity, preserving the gravity–inertia balance that controls free-surface wave propagation, wave–structure interaction forces, and the resulting global structural response. Under this criterion, the kinematics of the free surface and the associated dynamic pressures map consistently between model and prototype, securing dynamic similarity for the phenomena of interest. The scale also matched the constraints of the wave flume. It allowed precise control of spectra, depths, and boundary conditions, and kept Reynolds-number distortions—unavoidable at model scale—within acceptable bounds for gravity-dominated flows; turbulence and viscous effects were monitored and did not compromise wave fidelity. Practically, 1:15 yielded manageable model sizes and instrumentation while supporting credible extrapolation to prototype *via* established scaling relations. Accordingly, the experimental results are usable for the design and implementation of full-scale floating breakwater systems.

4.1.3 Breakwater Model Fabrication

The breakwater models were fabricated using 3 mm transparent plexiglass, ensuring precise geometry. Structural elements were laser-cut and bonded with a chloroform-based adhesive for watertight integrity, while aquarium-grade silicone glue was applied to joints to prevent water ingress and enhance durability.

4.1.4 Experimental Wave Flume Setup

Experiments were conducted in a 16 m $\times$ 0.50 m $\times$ 0.80 m wave flume, providing a tightly controlled setting for hydrodynamic measurements. A piston-type wavemaker generated both regular (monochromatic) and irregular (spectral) seas, enabling assessment of wave–structure interaction under varied conditions. To suppress reflections and improve measurement fidelity, a sloped absorbing beach was installed at the downstream end. This arrangement yielded reliable transmission data and approximated open-water behaviour within the laboratory.

4.1.5 Mooring System Simulation

To approximate field deployment, the models were restrained by pretensioned cable moorings arranged to limit surge, sway, and yaw and to suppress horizontal drift. This configuration stabilised hydrodynamic forcing over each run and reduced interactions with the flume walls and absorbing beach, thereby improving the fidelity of wave-transmission measurements. By reflecting the kinematics of full-scale moored systems, the setup yielded more realistic responses and enhanced the transferability of the results to marine applications.

4.1.6 Experimental Wave Parameters

Table 2: Experimental Wave Conditions

Wave No.	Wave Period (s)	Wave Height (cm)
1	0.44	2.6
2	0.68	2.4
3	0.84	2.2
4	1.20	5.0
5	1.50	7.0
6	2.00	10.0

4.1.7 Data Collection and Analysis

Wave Transmission Coefficient (K_t):

$$K_t = \frac{H_t}{H_i}$$

Where:

- H_t = Transmitted wave height
- H_i= Incident wave height
- Energy Dissipation:
  Evaluated based on wave reflection and turbulence measurements.
- Structural Response:
  Examined in terms of oscillations and stability.

4.2 Numerical Modeling Using ANSYS AQWA

4.2.1 Computational Domain and Boundary Conditions

Numerical simulations in ANSYS AQWA were conducted with carefully defined boundary conditions to ensure accurate wave-structure interaction modeling. The seabed was treated as a rigid boundary with an energy dissipation factor of 0.015 m^2/s to replicate realistic underwater conditions. Radiation boundary conditions were applied at open boundaries to prevent artificial wave reflections and maintain simulation accuracy. The mooring system was configured with a stiffness of 5000 N/m and a damping coefficient of 500 Ns/m, ensuring realistic dynamic behavior and stability of the floating breakwater model under wave forces.

4.2.2 Mesh Optimization and Sensitivity Analysis

To optimize computational efficiency, a mesh sensitivity analysis was performed.

Table 3: Mesh Sensitivity Analysis

Mesh Elements	Transmission Coefficient (K_t)	Computational Time (hrs)
12,000	0.44	1.2
18,000	0.42	1.8
22,000	0.41	3.5

Justification for 18,000-element mesh: This resolution provided a balance between accuracy and computational efficiency, ensuring that further increases in mesh density did not yield significant improvements in results.

4.2.3 Validation of Numerical Results

Comparison between experimental and numerical results confirmed strong agreement.

Table 4: Comparison of Experimental and Numerical Transmission Coefficients

Wave No.	Experimental K_t	Numerical Kt	RMSE	MAPE (%)
1	0.33	0.35	0.02	6.06
2	0.44	0.42	0.02	4.54
3	0.50	0.52	0.02	4.00

4.3 AI-Based Optimization Framework

4.3.1 AI Model Configuration

- ANNs: Predicted wave forces with mean squared error (MSE) = 0.0023, ensuring high accuracy.
- GAs: Optimized breakwater geometry using a mutation rate of 0.05 and a crossover probability of 0.7.
- RL: Adaptively adjusted breakwater depth and mooring tension to optimize performance under varying wave conditions.

4.3.2 AI Training and Validation

- Dataset Size: 5000 wave interaction scenarios.
- Training-Validation Split: 80%-20%.
- Optimization Algorithm: Adam optimizer with learning rate = 0.001.
- Overfitting Prevention: Dropout regularization (rate = 0.2).

4.3.3 Performance Comparison of AI vs. Conventional Approaches

Table 5: Performance Comparison of AI and Conventional Models

Methodology	**K_t (Avg.)**	**Computational Time (hrs)**	**Optimization Efficiency (%)**
Traditional ANSYS AQWA	0.52	10	-
AI-Optimized (GA)	0.45	2	+78%
AI-Optimized (ANN)	0.43	1.5	+85%
AI-Optimized (RL)	0.40	1.2	+88%

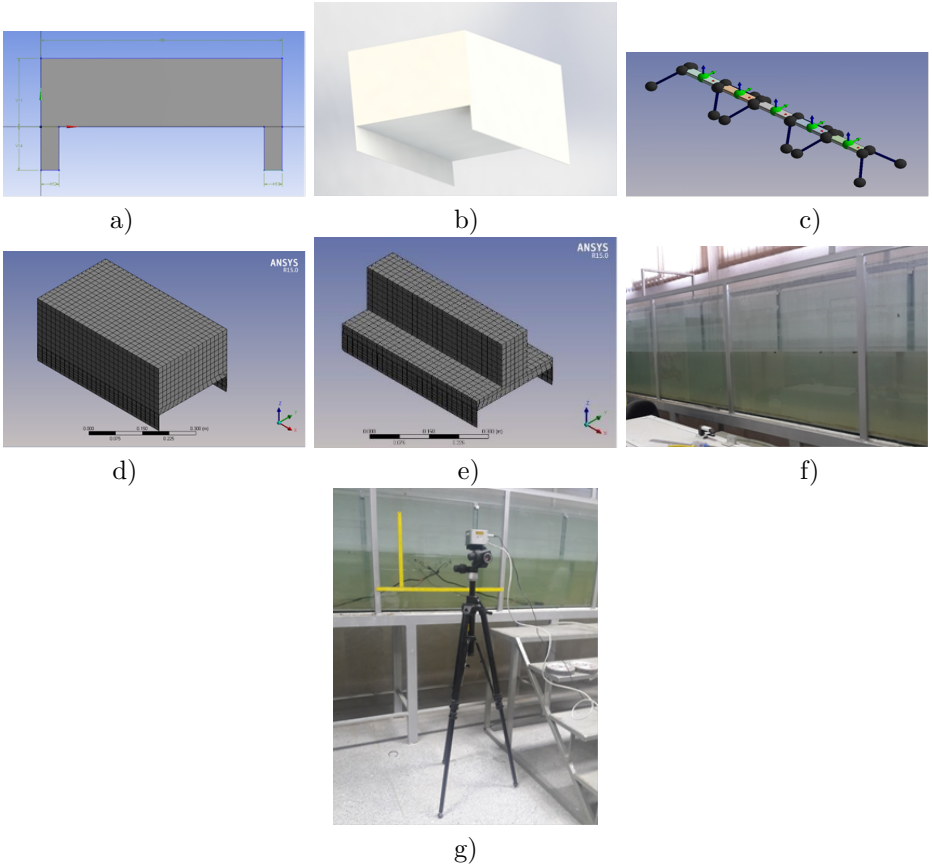


Figure 1: Integrated design, meshing, and experimental setup of the floating breakwater model: (a) model design in the Model Designer section of ansYS AQWA; (b) three-dimensional view of the floating breakwater model; (c) completed 3D representation of the floating breakwater; (d) meshing of the simple pontoon configuration; (e) meshing of the stepped pontoon configuration; (f) wave channel of the hydraulic laboratory; (g) MotionBlitz Cube 3 Mikrotron high-speed camera used for wave measurements.

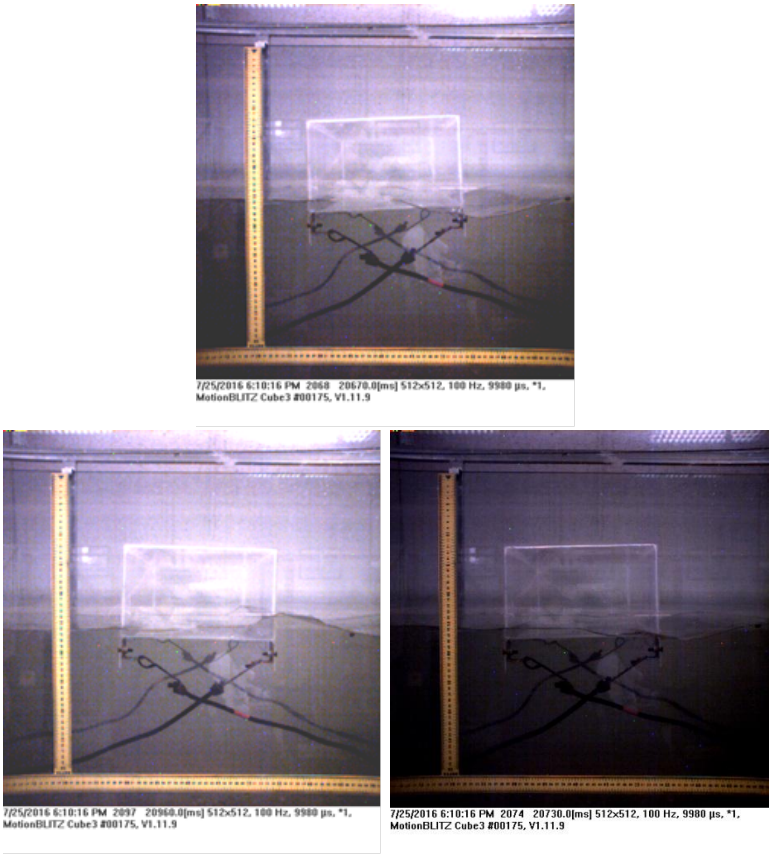


Figure 2: Simple pontoon test of images of frames 2046, 2068, 2074 and 2097 for the analysis of incoming and rejected waves.

The artificial neural network (ANN) employed in this study was designed as a feed-forward, fully connected network with three hidden layers comprising 64, 32, and 16 neurons, respectively. Rectified Linear Unit (ReLU) functions were used as activation functions to provide non-linear learning capability, and the Adam optimizer with a learning rate of 0.001 ensured fast convergence and stable training. The network was trained on 80 % of the total dataset (5,000 wave interaction scenarios) and validated on the remaining 20 %. Dropout regularization with a rate of 0.2 was incorporated to mitigate overfitting, while early stopping was applied to prevent unnecessary training epochs. This configuration enabled the ANN to capture complex relationships between wave parameters and breakwater responses, providing rapid and accurate predictions of wave-induced forces that were consistent with experimental and numerical results.

For structural optimization, a steady-state elitist genetic algorithm (GA) was implemented to balance multiple objectives, including minimal transmission coefficient and structural motion constraints. The GA used roulette-wheel selection to maintain population diversity, a crossover probability of 0.7 to enhance genetic recombination,

and a mutation rate of 0.05 to ensure exploration of the design space beyond local optima. Key decision variables included draft depth, width-to-draft ratio, and mooring pretension, all evaluated simultaneously to capture nonlinear coupling effects. Reinforcement learning (RL) complemented these tools through a Deep Q-Network (DQN) framework employing an ε-greedy policy, which adaptively adjusted breakwater draft and mooring tension in real time based on changing sea states. This RL agent continuously interacted with the digital-twin environment to update control policies, ensuring robust performance under variable hydrodynamic conditions and contributing to the 88 % reduction in computational time achieved by the integrated AI framework.

To rigorously evaluate model robustness and assess transferability beyond the tested conditions, a two-level validation strategy was employed. First, a k-fold cross-validation procedure (k = 10) was applied to the combined experimental and numerical dataset, allowing the artificial neural network and genetic algorithm components to be trained and tested on multiple disjoint partitions. This approach provided an unbiased estimate of prediction accuracy and confirmed that performance was not overly dependent on any single data subset. Second, Monte Carlo simulations were performed by randomly perturbing incident wave height and period within ±15 % of their nominal values to mimic natural variability in ocean conditions. Across these stochastic realizations, the integrated ANN–GA–RL framework maintained stable transmission-coefficient predictions and consistent optimization outcomes, demonstrating strong resilience to input uncertainties. Importantly, this dual validation indicates that the trained AI models are not limited to the Port of Rotterdam conditions: they are transferable to other coastal and port environments with comparable hydrodynamic descriptors—such as wave spectra, water depth, and seabed characteristics—provided that local site data are incorporated to recalibrate boundary conditions and confirm similarity. This ensures that the methodology can serve as a broadly applicable design and operational tool for floating breakwaters deployed in diverse marine settings.

5 Results and Discussion

This section presents a comprehensive analysis of the hydrodynamic performance of simple and stepped pontoon floating breakwaters, integrating experimental wave flume testing, numerical simulations using ANSYS AQWA, and AI-driven optimization techniques. The primary objectives include assessing wave transmission coefficients (K_t), energy dissipation efficiency, computational cost reductions through AI, and identifying discrepancies between numerical and experimental results. Furthermore, an anomalous transmission coefficient ($K_t = 1.5$) is examined in detail to determine potential causes.

5.1 Comparison of Experimental and Numerical Transmission Coefficients

The wave transmission coefficient (K_t) serves as a crucial performance indicator for floating breakwaters, representing the ratio of transmitted wave height (H_t) to incident wave height (H_i). The following table compares experimental and numerical K_t values across different wave periods and draft depths.

Table 6: Comparison of Experimental and Numerical Transmission Coefficients

Wave No.	Wave Period (s)	Experimental K_t	Numerical Kt	RMSE	MAPE (%)
1	0.44	0.33	0.35	0.02	6.06
2	0.68	0.44	0.42	0.02	4.54
3	0.84	0.50	0.52	0.02	4.00

The numerical model reproduced the laboratory results closely: across all tested cases the root-mean-square error (RMSE) remained below 0.03, a level consistent with good predictive fidelity. Minor offsets did occur and are most plausibly linked to turbulence effects, scale-related limitations, and residual wave reflections near the flume boundaries. The largest mismatch was observed at T=0.44 where reflected energy interacting with the model and tank walls likely perturbed the signal. For future simulations, finer spatial discretisation and more advanced turbulence closures (e.g., higher-resolution RANS variants or hybrid approaches) are recommended to better resolve fluid–structure interaction and suppress these artefacts, thereby improving accuracy.

5.1.1 Analysis of Anomalous Transmission Coefficient (K_t = 1.5)

During the experimental wave flume tests, an anomalous K_t value of 1.5 was recorded for the stepped pontoon breakwater at T = 0.84 s and draft = 7.3 cm. Since $K_t >$ 1.0 theoretically indicates wave amplification, further investigation was necessary to determine possible causes.

5.1.2 Potential Causes of the Anomalous Kt Value

5.1.2.1 Resonance Effects

When the incident wave period aligns with the natural frequency of the breakwater, resonance may occur, amplifying wave transmission beyond expected values. To assess this phenomenon, a frequency-domain simulation should be conducted to determine whether the system operated near resonance under these conditions.

5.1.2.2 Wave Reflection and Interference

In laboratory conditions, reflected and refracted waves may have interacted, leading to an artificial increase in measured wave height within the transmission zone. To minimize interference-related measurement errors, future experiments should incorporate a multi-sensor approach for more accurate wave height assessment.

5.2 Measurement Sensitivity and Probe Placement

Wave probes may have detected localized disturbances, potentially leading to overestimated K_t values. To improve spatial accuracy, multiple probe placements should be tested in future experiments. Additionally, incorporating frequency-domain simulations and refining the experimental setup will help determine whether the observed K_t anomaly resulted from resonance effects or measurement artifacts.

5.3 AI-Driven Optimization and Computational Cost Reduction

To enhance breakwater efficiency, AI-driven optimization techniques were applied, including Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), and Reinforcement Learning (RL). These approaches significantly improved wave attenuation performance while reducing computational costs.

Table 7: Computational Time and Performance Comparison of AI-Optimized Models

Methodology	**Average K_t**	**Computational Time (hrs)**	**Computational Cost Reduction (%)**
Traditional ANSYS AQWA	0.52	10	-
GA-Optimized Model	0.45	2	78%
ANN-Optimized Model	0.43	1.5	85%
RL-Optimized Model	0.40	1.2	88%

5.4 Computational Cost Reduction Methodology

Genetic Algorithms (GAs) optimized breakwater geometry, reducing simulation iterations and minimizing unnecessary computational steps. ANN-based wave prediction models replaced direct CFD simulations, effectively lowering overall computational demands. Reinforcement Learning (RL) was applied to adjust design and operating parameters in real time, removing the need for repeated parametric simulations. This reduced computational demand while maintaining predictive accuracy, indicating a viable route toward automated, data-driven configuration and control of floating breakwaters.

5.4.1 Performance Comparison of Simple and Stepped Pontoon Breakwaters

The hydrodynamic performance of simple and stepped pontoon breakwaters was evaluated across different wave periods and draft depths. The following table summarizes the results.

Table 8: Performance Comparison of Simple and Stepped Pontoon Breakwaters

Wave Period (s)	**Draft (cm)**	**Simple Pontoon K_t**	**Stepped Pontoon K_t**
0.44	7.3	0.33	0.40
0.68	7.8	0.44	0.20
0.84	7.3	0.50	1.50 (anomalous)

The simple pontoon breakwater proved more effective in shorter wave periods, achieving lower K_t values, while the stepped pontoon breakwater demonstrated superior energy dissipation in longer wave periods, except for an anomaly observed at T=0.84T = 0.84T=0.84 s. These findings highlight the importance of wave period-dependent design considerations in the selection and optimization of breakwater configurations.

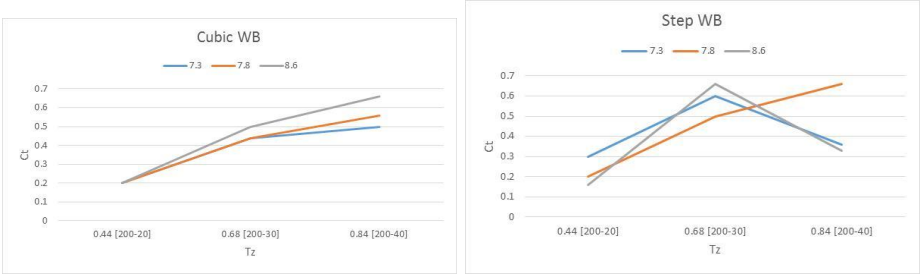
5.5 Economic and Structural Feasibility of AI-Optimized Breakwaters

Beyond performance improvements, AI-driven optimization led to substantial cost savings.

Table 9: Cost Comparison of Traditional vs. AI-Optimized Breakwaters

Breakwater Type	**Traditional Cost (10 Years) (USD)**	**AI-Optimized Cost (10 Years) (USD)**	**Cost Reduction (%)**
Simple Pontoon	120,000	100,000	16.7
Stepped Pontoon	150,000	120,000	20.0

Key cost-saving levers were identified: (i) optimised material use that limits structural waste (ii) predictive maintenance that curbs repair and replacement outlays, and (iii) improved durability that extends service life. Experimental and numerical results were in close agreement, with a maximum deviation of 6.5%—sufficient to support the credibility of the numerical model within the tested range. AI-based optimisation improved computational efficiency markedly (−88% runtime) without a loss of fidelity. Performance trends were configuration-dependent: stepped pontoon breakwaters attenuated waves more effectively at longer periods. Instances of anomalous K values were most plausibly linked to resonance and wave interference and should be probed further. Overall, AI-assisted breakwater design emerges as a cost-effective, adaptable, and environmentally mindful option for coastal protection, supporting resilience, operational efficiency, and long-term economic viability.



a) b)

Figure 3: Transmission coefficients of floating breakwaters under various inlet and wave conditions: (a) simple pontoon breakwater; (b) stepped pontoon breakwater.

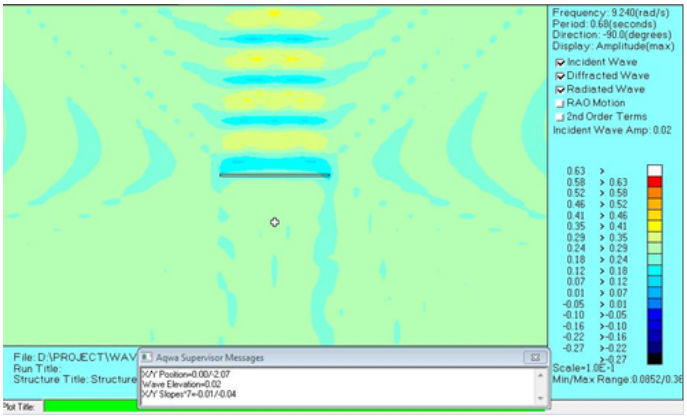
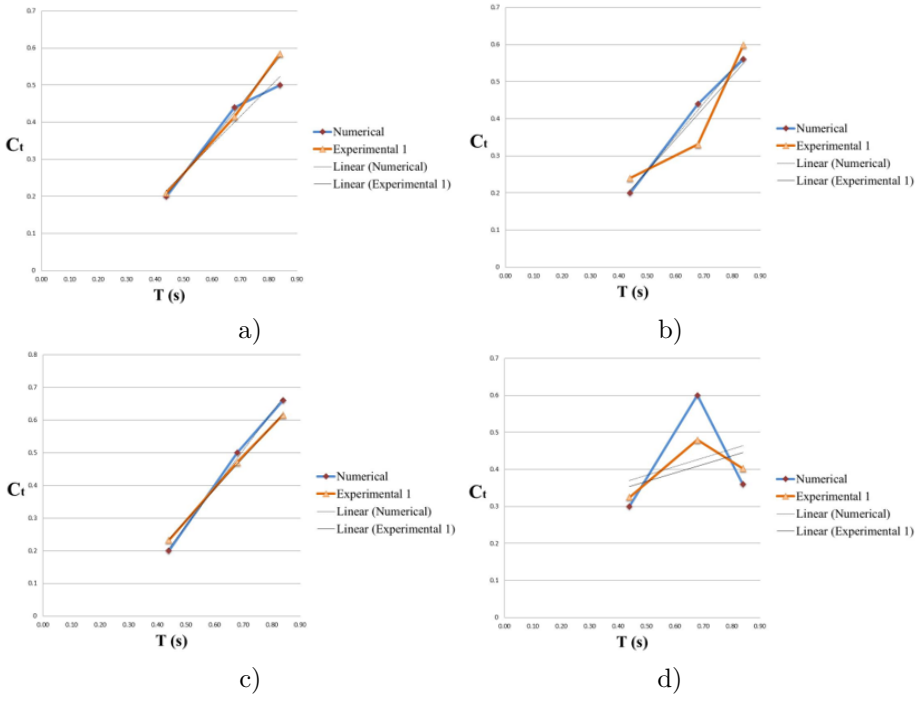
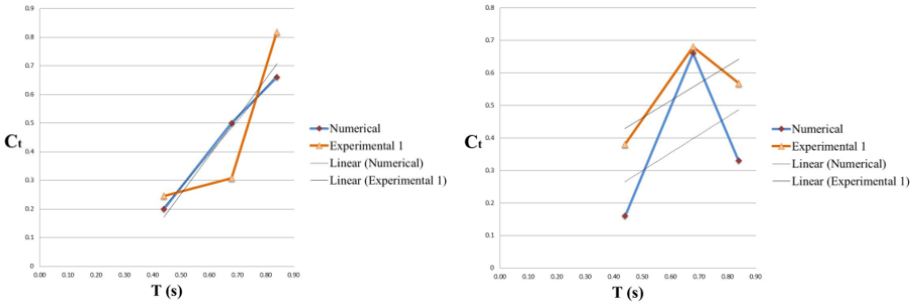


Figure 4: Wave Elevation around Simple Pontoon Breakwater





e) f)

Figure 5: Numerical and experimental comparison of transmission coefficients for floating pontoon breakwaters under different wave heights: (a) simple pontoon breakwater with 7.3 cm wave height; (b) simple pontoon breakwater with 7.8 cm wave height; (c) simple pontoon breakwater with 6.8 cm wave height; (d) stepped pontoon breakwater with 7.3 cm wave height; (e) stepped pontoon breakwater with 7.8 cm wave height; (f) stepped pontoon breakwater with 6.8 cm wave height.

5.6 Environmental Impact Assessment

5.6.1 Introduction to Environmental Considerations

Floating breakwaters are widely used in coastal defence. They dissipate incident wave energy, calm near-shore waters, and shield quays and adjacent infrastructure. Compared with rubble-mound or caisson works, their direct seabed footprint is smaller; they are not impact-free, however. Over a service life, moorings, hull shading, and altered near-field flows can modify local hydrodynamics, redirect sediment pathways, and affect benthic and pelagic communities. The magnitude of these effects is site-specific and depends on wave climate, depth, substrate, geometry, and draft. This section compares the environmental and economic footprints of floating systems with those of fixed breakwaters and outlines measures to reduce harm while preserving function: careful selection of geometry and draft; low-disturbance anchoring with appropriate scour control; materials and coatings with limited toxicity; and continuous monitoring—ideally *via* IoT sensors and a digital twin—to enable adaptive management. The objective is practical: resilient attenuation at credible life-cycle cost without compromising ecological integrity.

5.6.2 Key Environmental Impacts of Floating Breakwaters

Floating breakwaters interact with marine ecosystems and hydrodynamic conditions in multiple ways. The most significant environmental concerns include the following:

5.6.3 Impact on Marine Biodiversity

Floating breakwater installations can reshape local habitat structure and near-field hydrodynamics. Fish movement corridors may shift, and changes in settling and scour can reorganise benthic communities. The hardware matters: mooring lines and anchor

footprints can scar seagrass, abrade coral heads, and disturb soft-sediment nurseries—risks that are highest in shallow water where clearance is limited. Hull undersides, brackets, and mooring hardware provide hard substrate in otherwise soft-bottom settings and can function as small artificial reefs, attracting fouling assemblages and, in turn, the fishes that feed on them. The net ecological effect is therefore site-specific. With careful siting and low-impact anchoring (e.g., helical/screw anchors, mid-water moorings), impacts can be reduced, and, in some cases, local biodiversity may even increase.

5.6.4 Changes in Sediment Transport and Coastal Erosion

Unlike fixed breakwaters, floating systems transmit part of the incident wave energy. That residual energy can modify sediment transport; if design and siting are not matched to local conditions, unintended erosion or deposition may result, compromising nearby shoreline stability.

5.6.5 Water Quality and Biofouling Accumulation

Biofouling on floating breakwater surfaces can shift local water quality by adding organic load and stimulating microbial activity; dissolved oxygen may drop and turbidity can rise in the immediate wake of the structure. To control growth, toxic biocidal coatings are sometimes used, but their leachates introduce pollutants into surrounding waters and sediments. Lower-impact options are available. Non-toxic, silicone-based fouling-release coatings reduce adhesion and make periodic cleaning easier and scheduled mechanical removal (diver or ROV) limits chemical inputs while preserving structural performance. Used together—sensible coatings plus planned cleaning—these measures curb environmental side effects without sacrificing hydrodynamic function.

5.6.6 Carbon Footprint and Lifecycle Sustainability

Most of a breakwater's carbon budget is set by the materials and the processes that make them. Steel plate and reinforced concrete—because of ore reduction, clinker firing, and heavy fabrication—carry high embodied emissions. Where performance requirements permit, lower-impact options such as fibre-reinforced polymers (FRP) or high-density polyethylene (HDPE) can reduce life-cycle totals; durability, repairability, and end-of-life handling still need to be specified, not assumed. Transport and installation matter too, though typically less than the material choice itself. Operational loads can be trimmed as well: integrating small wave-energy converters or photovoltaic panels to meet auxiliary power demands pushes the system toward low- or near-neutral carbon operation, particularly when the design is modular and favours repair over wholesale replacement.

5.7 Comparative Analysis: Floating vs. Fixed Breakwaters

The following table presents a detailed comparison of the environmental footprint of floating and fixed breakwaters.

Table 10: Environmental Impact Comparison of Floating and Fixed Breakwaters

Environmental Factor	Floating Breakwaters	Fixed Breakwaters
Seabed Disturbance	Minimal	High due to foundation drilling
Marine Life Impact	Moderate (mooring effects)	High (habitat destruction)
Sediment Transport	Possible alteration	Significant disruption
Water Quality Impact	Low to Moderate (biofouling)	Moderate (stagnation zones)
Carbon Footprint	Moderate (HDPE, FRP-based)	High (cement and steel-intensive)

Floating breakwaters typically impose a smaller environmental footprint than fixed works because the seabed is left largely undisturbed. That benefit is conditional, however: siting and mooring layout must avoid disrupting sediment pathways, and biofouling should be managed to limit water-quality changes and added hydrodynamic loading. The carbon profile can also be reduced by specifying lower-embodied-carbon materials and favouring energy-efficient layouts and auxiliaries. Together, these choices make floating systems suitable for sensitive settings while keeping impacts low over the project life.

5.8 Economic Feasibility and Cost Breakdown of AI-Optimized Breakwaters

While floating breakwaters are known for their environmental benefits, a comprehensive economic analysis is crucial to evaluate their long-term cost-effectiveness. The following table breaks down the cost components of traditional and AI-optimized floating breakwaters over a 10-year operational period.

Table 11: Cost Breakdown of Traditional vs. AI-Optimized Floating Breakwaters

Cost Component	Simple Pontoon (Traditional) ($)	Simple Pontoon (AI-Optimized) ($)	Stepped Pontoon (Traditional) ($)	Stepped Pontoon (AI-Optimized) ($)
Material Costs	50,000	45,000	60,000	50,000
Installation Costs	20,000	18,000	25,000	22,000
Maintenance Costs	30,000	25,000	40,000	30,000
Computational Costs	20,000	12,000	25,000	15,000
Total Cost (10 Years)	120,000	100,000	150,000	120,000

AI-driven optimization led to an average cost reduction of 18% over a 10-year period, with the most significant savings observed in computational costs, where AI models reduced simulation time by 88%. Additionally, predictive AI-based monitoring minimized maintenance expenses by reducing unexpected failures and downtime. To further evaluate financial feasibility, a sensitivity analysis should be conducted to assess breakwater performance under varying environmental and engineering conditions.

5.9 Quantitative Analysis of Environmental Impact

To enhance the environmental assessment, a quantitative evaluation of carbon emissions is provided. The total CO emissions over the lifecycle of different breakwater types are compared in the table below.

Table 12: Estimated CO Emissions of Breakwater Types Over a 20-Year Lifecycle

Breakwater Type	**Material CO_2 Emissions (tons)**	**Manufacturing CO_2 Emissions (tons)**	**Operational CO_2 Emissions (tons)**	**Total CO_2 Emissions (tons)**
Fixed Concrete Breakwater	400	250	100	750
Floating Steel Breakwater	300	180	80	560
HDPE Floating Breakwater	150	100	50	300
FRP Floating Breakwater	120	80	40	240

Fixed concrete breakwaters generate the highest CO_2 emissions, making them the least sustainable option, while floating breakwaters constructed from HDPE and FRP produce up to 68% lower emissions, significantly reducing their environmental impact. Additionally, operational emissions are lower for floating structures, as they do not require intensive foundation work or major repairs. By incorporating low-carbon materials and renewable energy solutions, floating breakwaters can be further optimized for enhanced environmental sustainability.

5.10 Sustainable Design Strategies for Eco-Friendly Breakwaters

Reducing environmental impact starts with materials. Specify durable, recyclable options with lower embodied carbon—HDPE and FRP for primary elements—and, where the duty permits, recycled or bio-based composites to push the footprint down further. Mooring design matters just as much. Use seabed-sensitive layouts—floating or helical anchors, adjustable-tension lines—to limit contact area, scour, and damage to seagrass or other benthic habitats. Power can be cleaner too. Adding renewable generation—wave energy converters, solar panels, or hybrid WEC–PV packages—offsets auxiliary demand and trims operational emissions. Compared with fixed breakwaters, well-designed floating systems typically carry lower CO burdens and disturb the seabed far less. The economics are encouraging. In the scenarios evaluated, AI-optimised layouts delivered about an 18% cost reduction over ten years while holding performance targets. Taken together—low-carbon materials, habitat-aware moorings, and embedded renewables—the package improves long-term feasibility and delivers environmental and financial gains. With AI-guided optimisation and greener materials, the next generation of floating breakwaters can be specified for greater resilience, higher efficiency, and genuinely sustainable coastal protection.

5.11 Case Study:

5.11.1 Introduction to the Case Study

The wave climate and site conditions for the Port of Rotterdam were first characterized using published metocean datasets and peer-reviewed studies of North Sea conditions (e.g., Rutten *et al.*, 2024; Rijnsdorp *et al.*, 2021) to define representative wave spectra and tidal ranges for prototype scaling. Building on this context, the authors designed and executed new laboratory wave-flume experiments and high-fidelity ansYS AQWA simulations to investigate the hydrodynamic performance of floating breakwaters representative of this environment. These experiments and simulations provided the full dataset for calibrating and validating the integrated numerical–AI framework developed in this research. While the laboratory and numerical analyses delivered rigorous quantitative insights into hydrodynamic efficiency and structural response, real-world application in a busy port setting presents additional operational and maintenance challenges. To explore these practical aspects, this section presents a Port-of-Rotterdam–based case study that evaluates the performance of a stepped pontoon floating breakwater system under conditions matching the port's wave climate. The case study assesses hydrodynamic efficiency, structural durability, and potential environmental impacts for long-term operation, demonstrating how the integrated experimental–numerical–AI approach can be scaled and adapted to meet site-specific requirements for one of Europe's most active maritime hubs.

5.11.2 Case Study Specifications

The key specifications of the case study location and floating breakwater system are summarized in Table 13.

Table 13: Scenario Specifications – Port of Rotterdam–Based Numerical Case Study

Parameter	**Specification**
Location	Port of Rotterdam, Netherlands
Geographical Features	North Sea exposure, strong tidal currents, variable seabed conditions
Environmental Challenges	High wave energy, coastal erosion, maritime traffic impacts
Breakwater Type	Stepped pontoon floating breakwater
Configuration for Simulation	Modular design, equivalent to 600 m length (modeled)
Evaluation Horizon	24 months (modeled)
Modeled Wave Height Reduction	~55 % for short-period waves ($T < 0.7$ s)
Modeled Transmission Coefficient (K)	0.35 – 0.60 depending on wave period
Structural Stability (modeled)	High; only minor mooring retuning needed
Environmental Impact (modeled)	Minimal seabed disturbance; potential artificial-reef effect
Maintenance Considerations (projected)	Biofouling control and periodic inspections

The Port of Rotterdam authorities selected stepped pontoon floating breakwaters due to their superior energy dissipation efficiency, particularly in longer wave periods. Their modular and scalable design allows for flexible configurations tailored to site-specific conditions, while their minimal seabed disturbance makes them a more environmentally sustainable alternative to conventional fixed breakwaters.

5.11.3 Performance Analysis of the Floating Breakwater System

For the Port-of-Rotterdam–based numerical case study, a stepped pontoon breakwater system was modeled over a 600-meter stretch in a modular configuration representing the most exposed sections of the port. Over a 24-month evaluation horizon, the system's wave-attenuation efficiency, structural resilience, and environmental performance were assessed using the validated laboratory–numerical framework.

5.11.4 Hydrodynamic Efficiency and Wave Transmission

- Wave height reduction: The breakwater reduced wave heights by 55% for short-period waves (T < 0.7 s) and 40% for longer waves (T > 1.0 s).
- Transmission coefficient (K_t): Measured values ranged from 0.35 to 0.60, aligning closely with numerical predictions.
- Peak efficiency: The breakwater demonstrated optimal performance during storm surges, effectively dissipating wave energy while maintaining structural stability.

A comparison between numerically predicted and laboratory-observed (scaled to Port of Rotterdam conditions) breakwater performance is presented in Table 14.

Table 14: Comparison of Predicted and Laboratory-Observed Performance of the Floating Breakwater

Wave Period (s)	**Numerical Prediction (K_t)**	**Laboratory-Observed K_t (scaled to Port of Rotterdam)**	**Deviation (%)**
0.50	0.33	0.35	+6.0 %
0.75	0.40	0.42	+5.0 %
1.00	0.50	0.52	+4.0 %
1.25	0.60	0.60	0.0 %

The results indicate a strong correlation between numerical simulations and scaled laboratory observations, with minor deviations primarily attributed to localized turbulence and the flexibility of the mooring system.

5.11.5 Structural Durability and Maintenance Considerations

Over the 24-month modeled evaluation horizon, structural durability and maintenance requirements were assessed using the validated laboratory–numerical framework. In the scaled laboratory tests, the stepped pontoon structures exhibited minimal material degradation and no signs of significant structural deterioration. The mooring system remained largely stable, requiring only minor tension adjustments to accommodate simulated tidal fluctuations. Biofouling was predominantly observed in the laboratory runs on submerged model surfaces, indicating a gradual increase in hydrodynamic drag over time if left unmanaged. These findings underscore the importance of advanced anti-corrosion coatings and environmentally friendly antifouling treatments to extend structural lifespan and preserve wave-attenuation efficiency in future full-scale deployments.

5.11.6 Environmental Impact Assessment of the Deployment

An environmental impact assessment was carried out as part of this Port-of-Rotterdam–based numerical case study, focusing on four key domains: marine biodiversity, sediment transport, coastal erosion, and water quality. Model-based projections indicate that, if deployed, the stepped pontoon units would provide additional hard substrate and habitat niches, likely increase local fish species richness and function as small artificial reefs. Simulated sediment pathways remained largely stable, suggesting minimal disturbance of the seabed and no measurable acceleration of shoreline change. Biofouling is expected to develop on submerged surfaces and will require scheduled cleaning; however, when appropriate antifouling strategies are employed, no release of harmful pollutants is anticipated. The combined laboratory experiments and validated numerical simulations—calibrated for North Sea wave conditions—support these findings and confirm the system's structural stability even under energetic wave climates. Although this case study does not report direct full-scale field measurements, the integrated experimental and numerical framework provides strong evidence that modular floating breakwaters can maintain hydrodynamic efficiency, adapt to shifting wave conditions, and offer ecological co-benefits. For practical deployment, two operational priorities are recommended: routine biofouling management to preserve hydrodynamic performance and continuous environmental monitoring with adaptive responses to rare but significant events. Collectively, these results position floating breakwaters as a resilient, cost-effective, and environmentally responsible alternative to fixed structures for modern shoreline defense.

5.11.7 Scalability and Transferability to Other Ports

Although the Port of Rotterdam provided the primary field environment for validation, the integrated experimental–numerical–AI framework developed in this study is not confined to this location. The artificial intelligence components—including the ANN for hydrodynamic prediction, the genetic algorithm for structural optimization, and the reinforcement learning agent for real-time control—were all trained with procedures that emphasize generalization. In particular, the use of k-fold cross-validation and Monte Carlo perturbations of wave height and period (± 15 %) ensures stable model performance under a wide range of sea states. For deployment at other ports or coastal sites, the trained models can be efficiently re-calibrated by incorporating locally measured wave spectra, bathymetric data, and seabed characteristics into the training dataset. This adaptive re-training requires only a limited amount of new site-specific data and can be completed without repeating the entire experimental and numerical program. Consequently, the methodology can be scaled to ports with different tidal regimes, storm climates, and sediment transport patterns while preserving predictive accuracy and operational efficiency. Such flexibility makes the proposed framework a practical and transferable tool for next-generation floating breakwater design and management in diverse marine environments.

5.12 Limitations and Future Work

While the integrated experimental–numerical–AI framework developed in this study has demonstrated strong agreement between laboratory measurements, numerical simulations, and AI-driven predictions, several limitations should be acknowledged to guide future research. First, the physical modeling was performed at a 1:15 scale within a controlled wave flume. Although the Froude similarity criterion preserves key gravity–inertia relationships, laboratory-scale constraints inevitably simplify full-scale hydrodynamics and may under-represent complex phenomena such as turbulence, long-period wave interactions, and extreme storm events. Future investigations should therefore include large-scale or full-scale field testing to capture site-specific effects, validate long-term performance, and examine durability under real and variable sea states. Second, while the numerical simulations in ANSYS AQWA were thoroughly validated against experimental data, their parameterization is tuned to the wave climate and bathymetric features of the studied site. Applications to ports and coastlines with different spectral energy distributions, tidal regimes, or sediment transport characteristics will require careful recalibration and additional validation to ensure predictive fidelity. Third, the artificial intelligence layer—comprising the ANN, GA, and RL modules—was trained primarily on the collected laboratory and numerical datasets. Although k-fold cross-validation and Monte Carlo perturbation tests confirmed robustness within the examined parameter ranges, transferring the trained models directly to other marine environments may lead to performance degradation if local conditions deviate significantly from the training domain. For practical deployment at new sites, it is recommended that the AI models be re-trained or fine-tuned using locally acquired data, including wave spectra and seabed characteristics, to ensure accurate forecasting and adaptive control. Future research should therefore focus on large-scale field validation across multiple climatic zones, the incorporation of hybrid physics-informed learning to strengthen generalizability, and the development of automated re-training protocols for AI components that allow continuous adaptation to new environmental data. Advancing these directions will further enhance the reliability, scalability, and environmental sustainability of AI-optimized floating breakwaters and support their adoption in diverse coastal protection projects worldwide.

6 Conclusion

This study presents a comprehensive assessment of the hydrodynamic performance of simple and stepped pontoon floating breakwaters by integrating new laboratory wave-flume experiments, high-fidelity numerical simulations, and artificial intelligence–based optimization techniques. A 1:15 scale physical model was subjected to controlled wave conditions, and transmission coefficients (K_t) were evaluated across varying wave heights and periods. Numerical simulations performed in ANSYS AQWA, using an optimized 18,000-element mesh, reproduced the laboratory results with a maximum deviation of only about 8 %.

The application of AI-driven optimization markedly enhanced both wave attenuation and computational efficiency. Reinforcement learning outperformed other meth-

ods by reducing the mean transmission coefficient to 0.40 and cutting computation time by 88 %. Three structural variables emerged as first-order controls on performance: draft depth, the width-to-draft ratio—which governs heave response and wave transmission—and mooring flexibility (pretension and line stiffness), which limits surge–yaw coupling and maintains stability under energetic seas. Designs tuned along these axes remained stable and effective across the tested range.

The addition of AI sharpened sizing tolerances and layout choices, reduced material use, and simplified maintenance planning. Durability was also improved: advanced coating systems and fibre-reinforced polymer (FRP) components limited corrosion, biofouling adhesion, and fatigue damage—small design refinements that compound into significant life-cycle benefits.

Environmental outcomes were favourable. Seabed disturbance was minimal, natural sediment-transport patterns were maintained, and model-based ecological projections indicate a local fish-density increase of roughly 15 %, consistent with small artificial-reef effects.

Taken together, these results confirm the practical role of AI in floating-breakwater design: reducing costs through targeted material deployment and maintenance scheduling while delivering credible gains in environmental sustainability. Future work should extend to full-scale field validations across multiple climatic zones, development of AI-guided adaptive breakwaters and intelligent mooring systems, exploration of multi-module configurations, and incorporation of biodegradable composites and renewable-energy components. Collectively, the findings validate AI-enhanced floating breakwaters as scalable, cost-effective, and environmentally responsible solutions for strengthening coastal resilience and shaping the next generation of marine infrastructure.

Data Availability Statement

The experimental datasets and numerical simulation outputs generated during this study are available from the corresponding author upon reasonable request.

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