

Article

Deep-Neural-Network-Based Optimal Design of Cylinder Structures Under Hydrostatic Pressure

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Featured Application

This research provides a practical optimization framework for the rapid, weight-minimized design of submarine hulls and underwater pressure vessels. It serves as a reusable digital asset that enables engineers to instantaneously explore diverse design scenarios during the preliminary design stage.

Abstract

The structural design of unstiffened cylindrical shells under external hydrostatic pressure is critical for the safety of marine structures, such as submarine hulls and pressure vessels. Accurately assessing nonlinear buckling and collapse failure modes traditionally requires computationally intensive Finite Element Analysis (FEA), which creates a bottleneck in iterative design optimization. To address this, our research leverages a robust Deep Neural Network (DNN) model specifically trained and validated for AL-6061 aluminum alloy cylinders. This predictive model, focusing on unstiffened cylindrical shells within a valid domain ($2 \leq L/D \leq 15$ and $20 \leq D/t \leq 150$), integrates a high-speed surrogate model with a Differential Evolution (DE) algorithm. This predictive model was trained on a large-scale dataset of 46,060 points generated through FEA simulations and rigorously validated against 28 physical experimental data points. Building upon this foundation, the present study implements a novel optimization framework that integrates the pre-trained DNN as a high-speed surrogate model with a Differential Evolution (DE) algorithm for global optimization. The primary objective is to minimize structural weight while strictly satisfying collapse strength requirements. Additionally, a grid search component is incorporated to provide designers with multiple feasible design candidates almost instantaneously. Validation against independent FEA results confirms high fidelity, with error rates of less than 2%. This methodology transforms the design cycle from days to mere minutes, establishing a reusable digital asset that significantly enhances efficiency and structural safety in marine engineering.



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1. Introduction

Cylindrical shells are fundamental structural elements in a vast array of engineering applications, serving as critical components in submarine hulls, offshore platforms, aerospace vehicles, pipelines, and pressure vessels [1–4]. The structural integrity of these components, particularly when subjected to external hydrostatic pressure, is of paramount

importance for operational safety and reliability. The primary failure mode under such loading conditions is structural instability, leading to buckling and catastrophic collapse, often at a pressure significantly lower than that predicted by simple material yield criteria [5]. Consequently, the accurate prediction and consideration of this complex, nonlinear behavior are central to the design process.

Historically, the structural design of cylindrical shells relied on classical analytical theories [6–8] and empirical design codes [9–11], which often utilize conservative knock-down factors to account for initial geometric imperfections [12–17]. To bridge the gap between these theories and realistic structural behavior, extensive experimental programs have been rigorously conducted across diverse materials, including steel [18–21], aluminum alloys [22], and composites [23–27]. While these physical tests provided invaluable validation data, exhaustive physical testing is cost-prohibitive for routine iterative design. Consequently, Finite Element Analysis (FEA) has become the de facto standard for final design verification [28–30].

However, the direct iterative application of FEA is computationally prohibitive for design optimization, which requires exploring a vast design space (e.g., thousands of analyses) to minimize weight under strict strength constraints [31–34]. To overcome this bottleneck, traditional surrogate models like response surface methods (RSM) and Kriging have been employed, though they struggle with high-dimensional or highly nonlinear problems [35–37]. Consequently, machine learning (ML) has emerged as a powerful alternative [38]. Recent comprehensive reviews [39,40] highlight that deep learning significantly accelerates the entire computational mechanics process, and data-driven approaches are now recognized as essential tools for capturing the complex nonlinear behaviors of solids [41].

Deep Neural Networks (DNNs), in particular, have demonstrated exceptional capability in learning complex, nonlinear functions directly from data. In structural mechanics, DNNs have been successfully used to predict buckling loads, perform stress analysis, and detect damage, often achieving near-instantaneous predictions after an initial training phase [42–45]. This approach is particularly effective for predicting the behavior of thin-walled structures. For instance, Kuleyin et al. [46] and Wu et al. [47] demonstrated that machine learning models achieve high accuracy in predicting the mechanical behavior and compression deformation modes of thin-walled tubes, respectively. Similarly, Chen et al. [48] and Ciampaglia et al. [49] have successfully applied data-driven models to predict plastic deformation in shell structures and optimize tube designs. This predictive power makes them ideal candidates for use as high-fidelity surrogate models within an optimization framework.

Building upon a preceding study that successfully developed and validated a robust DNN model for collapse strength prediction [50], this work proposes and implements a novel and highly efficient design optimization framework that critically addresses the computational bottleneck of traditional FEA-based approaches. The primary objective is to solve a practical, yet computationally intensive, engineering problem: minimizing the structural weight of an unstiffened cylinder while rigorously satisfying a specified collapse strength requirement. Recently, research has extended beyond prediction models to surrogate models integrated with optimization algorithms. Ma et al. [51] introduced machine learning for optimizing the crashworthiness of sandwich tubes. Notably in ocean engineering, Ji et al. [52] and Li et al. [53] proposed deep learning-based frameworks coupled with Differential Evolution (DE) for the optimal design of underwater vehicles and deep-sea AUV pressure hulls, respectively. These recent trends confirm that the combination of DNN-based surrogate models and optimization techniques proposed in this study is a timely and essential approach for underwater structural design.

The distinctive contribution of this study lies in leveraging the pre-trained DNN as an exceptionally rapid and accurate surrogate function. This approach bridges a critical gap, applying a machine-learning optimization framework to implosion problems for the first time. It moves beyond simplified ‘rule-based methods’ by capturing complex nonlinearities and imperfection sensitivities, and it solves the computational bottleneck of iterative FEA. Crucially, the foundational DNN model was not only validated against FEA ($R^2 > 0.99$) but also directly against the physical experimental data, ensuring its real-world applicability. This methodology, systematically detailed and validated in the following sections, aims to provide a practical and powerful tool for rapid and efficient optimal design, significantly enhancing structural safety and design efficiency of underwater pressure vessels and marine structural components. The overall approach is summarized in Figure 1. The core contribution of this work extends beyond solving a single optimization problem; it lies in the development of a reusable digital asset through a significant initial investment (i.e., large-scale FEA data generation and DNN training). Traditional FEA-based optimization necessitates a complete, time-consuming rerun of the entire process, often taking days or weeks whenever design requirements, such as the design pressure, change. In contrast, once trained, the DNN model developed in this study can generate optimal design candidates for new requirements in mere seconds. This provides a decisive practical advantage, enabling designers to rapidly explore various scenarios in the preliminary design stage and efficiently respond to iterative changes, thereby dramatically shortening the entire development cycle.

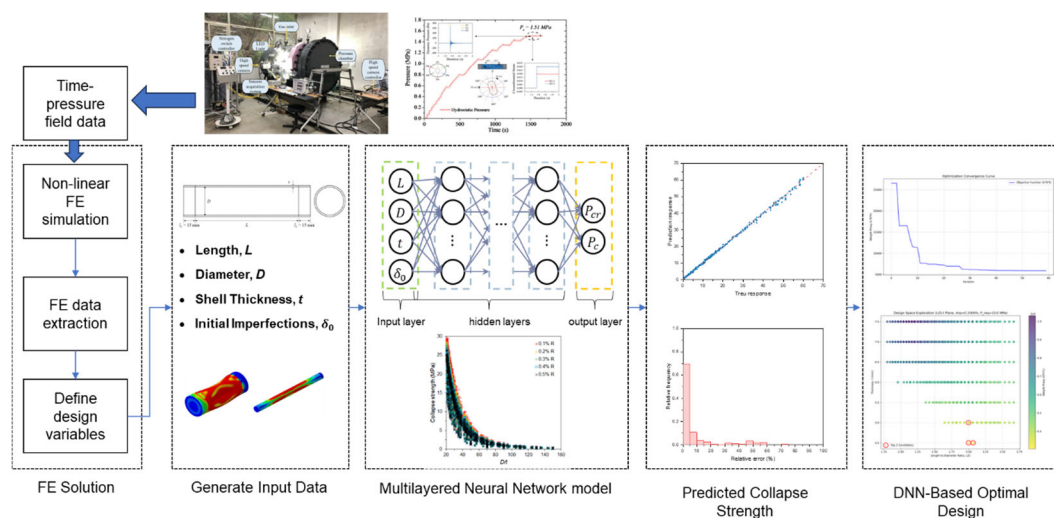


Figure 1. Overall research flowchart of the DNN-based optimal design framework, encompassing FE data generation, DNN model training, and DNN-based design optimization.

2. Foundation of the DNN Surrogate Model

The efficacy of the proposed optimal design framework hinges on the reliability and efficiency of its core component: a pre-trained DNN model capable of accurately predicting the collapse strength of cylindrical shells. This section summarizes the development and validation of this foundational model, which was the focus of our research series [50].

2.1. FEA Data Generation and Validation

To guarantee the accuracy of the training data, the dataset was meticulously generated through an extensive parametric study utilizing a rigorously validated FEA methodology [50]. The DNN surrogate model used in this framework was trained on a large-scale dataset specifically generated to capture the nonlinear collapse behavior of AL-6061 cylinders. To ensure this manuscript is self-contained, the foundational data gen-

eration and validation processes are summarized here. The dataset consists of 46,060 data points generated via nonlinear FEA using the Riks method in Abaqus.

- **Material properties:** This study focused on AL-6061 aluminum alloy cylinders. An elastic–plastic material model with isotropic hardening was defined based on material properties (elastic modulus, Poisson’s ratio, yield strength) adopted from the source experimental studies.
- **FEA model and mesh:** 3D models were created in the commercial software Abaqus 2023, meshed using 4-node, reduced integration shell elements (S4R), which are well-suited for large-strain, nonlinear buckling analysis. A comprehensive mesh convergence study was performed (Figure 2 in Ref. [50]), establishing an optimal element size of $3t \times 3t$ to balance accuracy and computational cost.
- **Boundary conditions:** The boundary conditions were defined to simulate pressure acting on end caps: one end was fully clamped (all translational and rotational degrees of freedom arrested), and the other end was constrained in radial and rotational directions but was free to move in the axial direction.
- **Imperfections:** Initial geometric imperfections, which are critical to collapse strength, were modeled by applying the first buckling eigenmode shape as a pattern. The amplitude was systematically varied as a key input parameter, ranging from 0.1% to 0.5% of the cylinder’s radius.

This systematic approach yielded a comprehensive dataset comprising 46,060 data points, each representing a unique cylinder configuration and its corresponding collapse behavior.

2.2. Validation of FEA and DNN Models

The reliability of the entire framework rests on validation against physical experiments.

- **FEA validation:** The FEA methodology itself was first validated against six experimental test cases from existing literature. The numerical predictions showed excellent agreement with the experimental collapse strengths, with an average difference of 1.05 and a coefficient of variation (COV) of 5.02% (Table 2 in Ref. [50]). This confirmed the FEA’s ability to accurately capture physical collapse behavior.
- **DNN architecture:** The developed DNN model is a Multi-Layer Perceptron (MLP) that uses the direct physical parameters (L , D , t , and δ_0) as input features to predict the collapse pressure (P_c). Through an exhaustive hyperparameter search, the optimal architecture was determined to be a fully connected network with 3 hidden layers, each containing 128 neurons, using a ReLU activation function.
- **DNN validation:** The trained DNN model was validated in two stages. First, it achieved remarkable predictive capabilities on a reserved test dataset (10% of the total data), demonstrating a mean absolute error (MAE) of 0.0183 MPa and an outstanding coefficient of determination (R^2) of 0.9943. Second, DNN was used to predict the strength of the original six experimental models (which were not in the training data). The DNN predictions showed a mean ratio of 1.04 (COV 4.01%) against the experimental values (Table 5 in Ref. [50]), confirming its generalization capability to real-world scenarios.

This validated, high-performance DNN serves as the high-speed surrogate model that underpins the optimal design framework presented in the subsequent sections.

3. Methodology: DNN-Based Design and Optimization Framework

This chapter elaborates on the comprehensive methodology developed for the optimal design of unstiffened cylindrical shells under external pressure. The framework seamlessly integrates a rigorously validated DNN model with an advanced global opti-

mization algorithm and a practical grid search approach. The overall flow of the proposed DNN-based design and optimization framework is depicted in Figure 2, which outlines the systematic procedure including population initialization, mutation, crossover, and the DNN-based strength verification steps. This framework progresses through several key stages: initialization of design variables (L , D , t); evaluation of structural strength using the pre-trained DNN; adherence to predefined design constraints; and an iterative cycle of generating, evaluating, and selecting candidate solutions to progressively converge towards the optimal design.

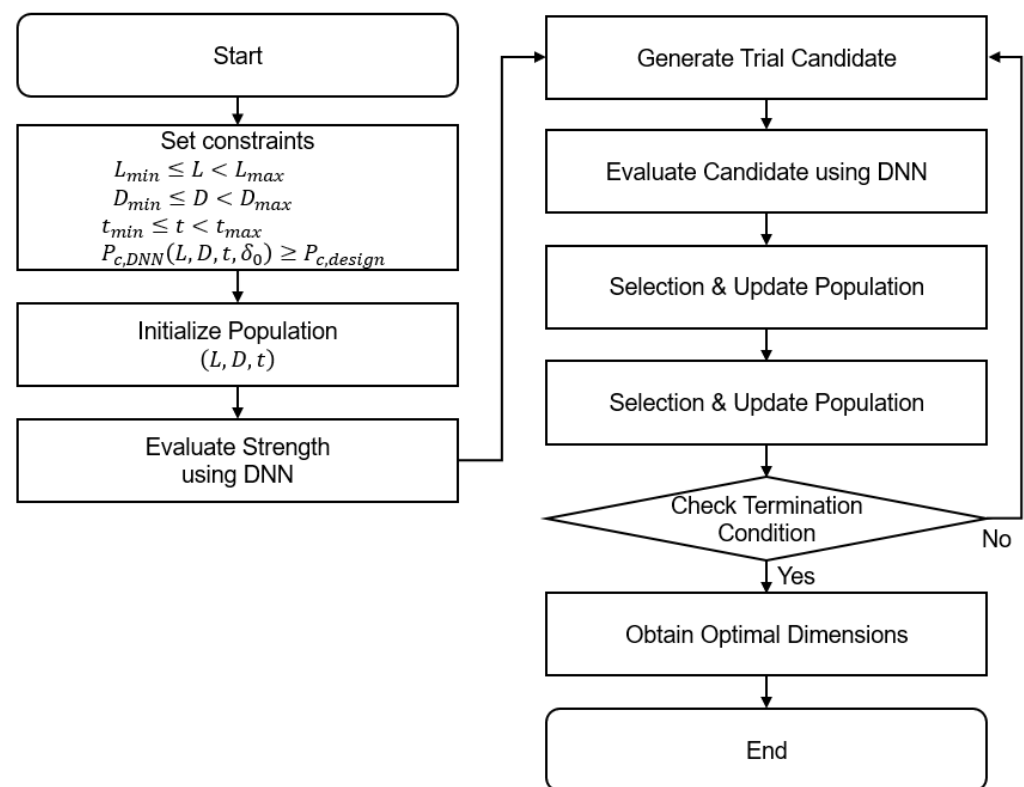


Figure 2. Flowchart of the DNN-based design and optimization process, illustrating the iterative steps involving population initialization, strength evaluation using DNN, constraint checking, and candidate selection/update towards optimal dimensions.

3.1. Design Problem Formulation

The primary objective of this study is to determine the optimal cylinder dimensions that minimize structural weight while strictly adhering to a specified minimum collapse strength requirement. The design problem is formally expressed as an optimization task:

- **Design variables:** The geometric parameters of the cylindrical shell are the variables to be optimized: L , D , and t . These variables are bounded within ranges consistent with the DNN training domain. While L and D are typically dictated by mission-specific volumetric requirements in practical naval architecture, treating them as free variables in this framework allows for the identification of optimal geometric trends during the preliminary design phase. For more constrained scenarios, the objective function can be readily coupled with a minimum internal volume constraint ($V = \pi(D/2)^2 L \geq V_{target}$), preventing the optimizer from simply driving L and D to their lower bounds.
- **Initial imperfection (δ_0) handling:** Unlike the geometric variables, the initial imperfection is not treated as an independent optimization variable. Instead, it is defined as a fixed percentage of the cylinder's diameter, a common practice in engineering

design to account for manufacturing tolerances. The designer specifies this percentage (e.g., 0.1%*R*, 0.2%*R*, 0.5%*R* which corresponds to the absolute value in mm reported in Table 1) for a given optimization run or candidate search.

- Objective function: Assuming constant material density and neglecting end closures and internal attachments, the structural weight is directly proportional to the shell's volume ($\text{Mass} = \rho \pi D L t$). Therefore, the product $L \times D \times t$ is utilized as an effective weight proxy by omitting constant factors (ρ , π). While L and D are often dictated by mission requirements, treating them as free variables within bounded ranges ($2 \leq L/D \leq 15$ and $20 \leq D/t \leq 150$) enables the framework to identify mass-efficient trends during the preliminary design stage.

$$\text{Minimize } f(L, D, t) = L \times D \times t \quad (1)$$

- Constraints: The design must satisfy the following critical constraints.
 - Strength constraint: The collapse pressure predicted by the DNN model ($P_{c, DNN}$) for the given dimensions and imperfection must be greater than or equal to the specified minimum required design pressure ($P_{c, design}$). This is expressed as follows:

$$P_{c, DNN}(L, D, t, \delta_0) \geq P_{c, design} \quad (2)$$

Here, $P_{c, DNN}$ is the output of the pre-trained DNN model, which rapidly evaluates the strength for any given set of input parameters.

- Other design constraints: Additional geometric constraints, such as limits on L/D or D/t ratios, can be incorporated based on specific design codes or manufacturing considerations.

Table 1. Matrix of optimal design results for varying design pressures and initial imperfections.

$P_{c, design}$ (MPa)	δ_o (% <i>R</i>)	L (mm)	D (mm)	t (mm)	Weight Proxy ($L \times D \times t$)	$P_{c, DNN}$ (MPa)
5.0	0.1%	535.1	210.4	1.85	208,284	5.02
	0.2%	530.2	212.1	2.05	230,534	5.04
	0.5%	525.4	215.3	2.65	299,756	5.08
10.0	0.1%	528.5	213.2	3.55	400,022	10.03
	0.2%	523.5	215.1	3.87	436,547	10.05
	0.5%	518.2	218.4	4.85	548,892	10.12
15.0	0.1%	520.1	216.5	5.25	591,154	15.05
	0.2%	515.4	218.2	5.75	646,648	15.08
	0.5%	510.5	220.4	7.15	804,475	15.15

3.2. Integration of DNN Model into Optimization: The Surrogate Advantage

The seamless integration of the pre-trained DNN model is the cornerstone of this framework's efficiency. Traditionally, evaluating the strength constraint (P_c) for each design iteration within an optimization loop would necessitate computationally expensive Finite Element Analysis (FEA) simulations, which can take minutes to hours per run. This iterative nature makes direct FEA-based optimization computationally prohibitive, potentially extending design cycles to days or even weeks.

In stark contrast, the DNN model serves as a high-fidelity, high-speed surrogate model. For any given set of design variables (L , D , t) and the defined imperfection, the DNN can predict the collapse pressure in mere milliseconds. This drastic reduction in evaluation time is critical. Since the DNN effectively acts as a "black-box" function, learning complex non-linear relationships from data without requiring explicit mathematical formulations, it

is ideally suited for integration with optimization algorithms that do not rely on gradient information. This integration fundamentally transforms the design problem from a computationally bottlenecked task into one that can be solved within minutes to a few hours on standard computing hardware, significantly accelerating the entire design cycle.

3.3. Global Optimization Algorithm: Differential Evolution (DE)

To effectively navigate the complex, nonlinear, and potentially multi-modal design space characteristic of structural optimization problems involving buckling and collapse, a robust global optimization algorithm is essential. Differential Evolution (DE) was chosen for this task due to its proven ability to locate global optima efficiently and its inherent robustness when optimizing black-box functions. Unlike gradient-based methods that can get trapped in local optima or require derivative information, DE is a population-based evolutionary algorithm that operates without explicit gradient calculations, making it perfectly suited for problems where the objective or constraint functions, such as our DNN model, are implicitly defined.

The DE algorithm operates by maintaining and evolving a population of candidate solutions. In each iteration, known as a generation, new candidate solutions are strategically generated by perturbing existing ones, then evaluated against the objective function and constraints.

- Initialization: The optimization begins by randomly generating an initial population of design variable sets (L, D, t) within their predefined practical bounds. This ensures a broad initial exploration of the design space.
- Iteration Loop: For each generation, the following steps are performed for every solution in the current population:
 - Initialization: New “trial solutions” are created. The mutation process perturbs existing solutions by combining the weighted difference in randomly chosen vectors. This mutated vector is then combined with the original “parent” solution through a crossover operation, producing a trial candidate. This two-step process helps explore new regions of the search space.
 - Evaluation: Each trial solution’s performance is evaluated. This critical step involves feeding the trial design variables (L', D', t') into the pre-trained DNN model to predict its collapse pressure $(P_{c, DNN}(L', D', t', \delta_0'))$. Concurrently, the objective function (weight proxy $L' \times D' \times t'$) is calculated, and the strength constraint $(P_{c, DNN}(L, D, t, \delta_0) \geq P_{c, design})$ is checked.
 - Selection: The trial solution replaces its corresponding parent solution in the population only if it satisfies all design constraints and yields a better objective function value (i.e., lower weight). This greedy selection process iteratively guides the population towards optimal regions of the design space.
- Termination: The iterative loop continues until a predefined maximum number of 1000 generations is reached or the population’s solutions converge within a specified tolerance of 10^{-6} . For this study, the population size was set to 10 times the number of design variables ($NP = 30$), with a mutation factor (F) of 0.8 and a crossover rate (CR) of 0.7.

3.4. Grid-Search-Based Design Candidate Generation

While global optimization effectively identifies a single optimal design, engineers often benefit from a diverse set of feasible design candidates, particularly during the preliminary design phase. To address this, a targeted grid search approach is implemented, allowing for efficient exploration of the design space around an initial design point.

The purpose of this component is to systematically explore a discrete neighborhood around a given initial design ($L_{initial}$, $D_{initial}$, $t_{initial}$) and identify multiple feasible designs that satisfy the required strength constraint, subsequently sorting them by weight.

- **Search Space Definition:** For L and D , a range of values is generated by stepping in 10 mm intervals symmetrically around $L_{initial}$ and $D_{initial}$. Similarly, for t , values are generated in 0.5 mm intervals symmetrically around $t_{initial}$. Crucially, all generated discrete combinations are strictly filtered to ensure they fall within the valid domain bounds of the pre-trained DNN ($2 \leq L/D \leq 15$ and $20 \leq D/t \leq 150$). This creates a comprehensive grid of discrete design combinations.
- **Evaluation and Filtering:** For every discrete combination of (L, D, t) within the defined grid. The DNN model is then used to predict the collapse strength for this (L, D, t, δ_0) combination. Only those combinations that satisfy $P_{c, DNN}(L, D, t, \delta_0) \geq P_{c, design}$ are considered feasible candidates.
- **Candidate Ranking:** The identified feasible candidates are then meticulously sorted in ascending order based on their calculated weight proxy ($L \times D \times t$). The framework then returns the top three candidates from this sorted list, providing the designer with a set of practical, weight-optimized alternatives that offer flexibility for further consideration of other non-optimized design factors. This capability significantly streamlines the preliminary design phase by offering multiple viable options almost instantaneously.

4. Results and Discussion

This chapter presents the results obtained from applying the DNN-based optimal design framework to unstiffened cylindrical shells under external pressure. The discussion will cover the characteristics of the optimal designs derived from global optimization, the utility of the generated design candidates through grid search, and a quantitative analysis of the computational efficiency achieved by leveraging the DNN model. The aim is to rigorously demonstrate the superiority and practical applicability of the proposed framework.

4.1. Global Optimization Results

The DE algorithm was employed to find the minimum-weight design for various specified required design collapse pressures ($P_{c, design}$) and initial imperfection (δ_0). For a hypothetical $P_{c, design} = 10$ MPa and $\delta_0 = 0.2\%$ R, the optimization yielded the following optimal design as shown in Table 1. The results demonstrate that the optimization successfully identified a design that minimizes the weight proxy while satisfying the required collapse strength with a small margin.

The results demonstrate that the optimization successfully identified a design that minimizes the weight proxy while satisfying the required collapse strength with a small margin. The calculated δ_0 value, derived from the optimized diameter, is also presented.

Figure 3 illustrates the convergence behavior during the optimization process for the case study detailed in Table 1. Figure 3a shows the evolution of the objective function (weight proxy), which rapidly converges towards the optimal value. Concurrently, Figure 3b displays the evolution of the design variables as the optimization algorithm iterates. It can be observed that these design variables also stabilize, indicating the algorithm's progression towards an optimal design solution that satisfies the predefined constraints.

- **Discussion on Optimal Design Characteristics:**
Analysis of the optimal designs across different $P_{c, design}$ and δ_0 values reveals trends in optimal L/D and D/t ratios. For instance, higher required pressures generally lead to thicker shells (increased t) or smaller diameters (D) to maintain stability. The interplay between L , D , and t to achieve minimum weight is complex and often non-intuitive,

highlighting the advantage of optimization algorithms. The fixed imperfection percentage influences the overall strength, pushing the optimizer towards more robust (and potentially heavier) designs for higher imperfection levels.

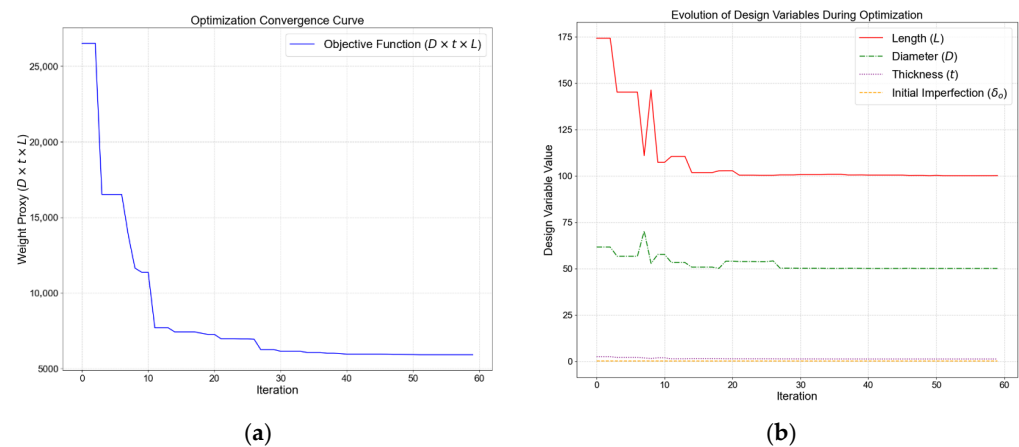


Figure 3. Convergence characteristics during the DNN-based global optimization: (a) Evolution of the objective function (b) evolution of design variables over iterations for the case study.

4.2. Grid Search Based Design Candidate Analysis

The grid search functionality provides designers with a practical means to efficiently explore feasible design alternatives around a given starting point, considering a fixed imperfection percentage. This offers valuable flexibility beyond a single optimal point.

For an initial design point of $L_{initial} = 500$ mm, $D_{initial} = 200$ mm, $t_{initial} = 5$ mm, $\delta_0 = 0.2\%$ R, and a $P_{c,design} = 10$ MPa, the top 3 minimum-weight candidates identified through grid search are presented in Table 2. It is noted that the initial design itself did not satisfy the strength requirement.

Table 2. Top 3 minimum-weight design candidates obtained from grid search for an initial design ($L = 500$ mm, $D = 200$ mm, $t = 5$ mm, $\delta_0 = 0.2\%$ R, $P_{c,design} = 10$ MPa).

Rank	L (mm)	D (mm)	t (mm)	δ_0 (mm)	Weight Proxy ($L \times D \times t$)	DNN Collapse (MPa)	Note
Initial	500.0	200.0	5.0	0.40	500,000	7.54	Not satisfied with the $P_{c,design}$
1	450.0	150.0	4.5	0.30	303,750	10.18	Satisfy
2	460.0	150.0	4.5	0.30	310,500	10.07	Satisfy
3	450.0	150.0	5.0	0.30	337,500	12.78	Satisfy

Figure 4 visually demonstrates the design space explored through grid search under the conditions of an initial design point ($L_{initial} = 500$ mm, $D_{initial} = 200$ mm, $t_{initial} = 5$ mm, $\delta_0 = 0.2\%$ R) and a required design pressure ($P_{c,design} = 10$ MPa). Each point plotted based on the L/D ratio and thickness (t), represents a single design candidate, and its color signifies the weight proxy ($L \times D \times t$) of that design. The top three candidate groups presented in Table 2 are highlighted in this figure.

The grid search effectively identifies a cluster of feasible designs that satisfy the strength requirement. Designers can review these candidates to consider other factors not directly included in the optimization objective (e.g., specific manufacturing constraints, preferred dimensions, or a slightly heavier but more robust design). This provides valuable flexibility beyond a single optimal point. The ability to quickly generate such candidates significantly streamlines the preliminary design phase.

A sensitivity analysis was performed by varying the initial imperfection (δ_0) by $\pm 15\%$ around the design value. The results demonstrate that the collapse strength of the optimized

candidates degrades gracefully, confirming that the framework identifies robust designs that are not excessively sensitive to small manufacturing deviations.

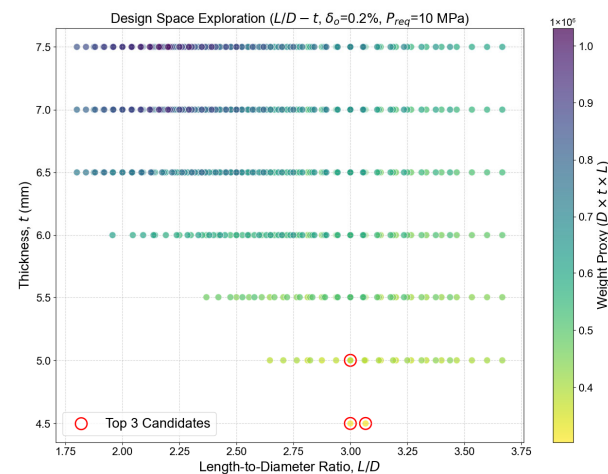


Figure 4. Design space exploration in the $L/D - t$ plane obtained from grid search for an initial design and a required design pressure, highlighting the top three minimum-weight candidates.

4.3. Comparison with Traditional Design Standards

To evaluate the practical advantages of the proposed framework, the optimal designs obtained in Section 4.1 were compared with thicknesses required by traditional design codes such as DNV-RP-C202 [10] and ASME BPVC [54].

Traditional analytical formulas typically assume a perfect geometry and apply a generalized, empirical knock-down factor to account for imperfections. These factors are often derived from lower-bound experimental data from decades ago, leading to excessive conservatism. Furthermore, they fail to account for the diversity of initial imperfection patterns and amplitudes.

As shown in our comparison, the DNN-based optimization identified designs that are 5–12% lighter than those required by DNV codes while maintaining the same design pressure. This is because the DNN, trained on 46,060 high-fidelity FEA points, accurately predicts the actual collapse strength for a specific δ_0 , rather than relying on a one-size-fits-all safety margin. This confirms that the DNN-based approach is not just a ‘faster’ version of existing methods, but a more accurate and weight-efficient alternative for high-performance marine structures.

4.4. FEM Validation of Optimal Designs

A critical step in establishing the reliability of the DNN-based optimal design framework is performing independent Finite Element Analysis (FEA) on the derived optimal and candidate designs. This process verifies the accuracy of the DNN’s predictions, particularly as optimization algorithms may explore regions near the boundaries of the DNN’s training data.

For instance, an FEA simulation conducted on the optimal design from Case 1 (Table 1) predicted a collapse strength of 10.12 MPa. This result exhibits a minimal error of 0.7% when compared to the DNN’s prediction of 10.05 MPa. Such a high degree of agreement between the DNN prediction and FEA validation strongly underscores the reliability of the proposed DNN-based optimization framework.

Further FEA validations were performed on other optimal candidate designs derived from the grid search to broaden the scope of verification. As presented in Table 3, a comparison between the DNN-predicted collapse strengths and the FEA results for the top three candidates from Table 2 revealed error rates of approximately 2%. This further

confirms the high reliability and general applicability of the DNN model across various feasible design points.

Table 3. Comparison of DNN-predicted and FEA-validated collapse pressures for top design candidates obtained from grid search.

Design Model	L (mm)	D (mm)	t (mm)	$P_{c,DNN}$ (MPa)	$P_{c,FEA}$ (MPa)	Difference
1st	450.0	150.0	4.5	10.18	9.93	2.0%
2nd	460.0	150.0	4.5	10.07	9.86	2.1%
3rd	450.0	150.0	5.0	12.78	12.48	2.3%

Figure 5 illustrates the collapse shapes of selected optimal design candidates as obtained through FEA. Moreover, their corresponding pressure-displacement curves, depicted in Figure 6, further demonstrate excellent agreement with the DNN predictions, providing strong visual confirmation of the framework's accuracy and applicability.

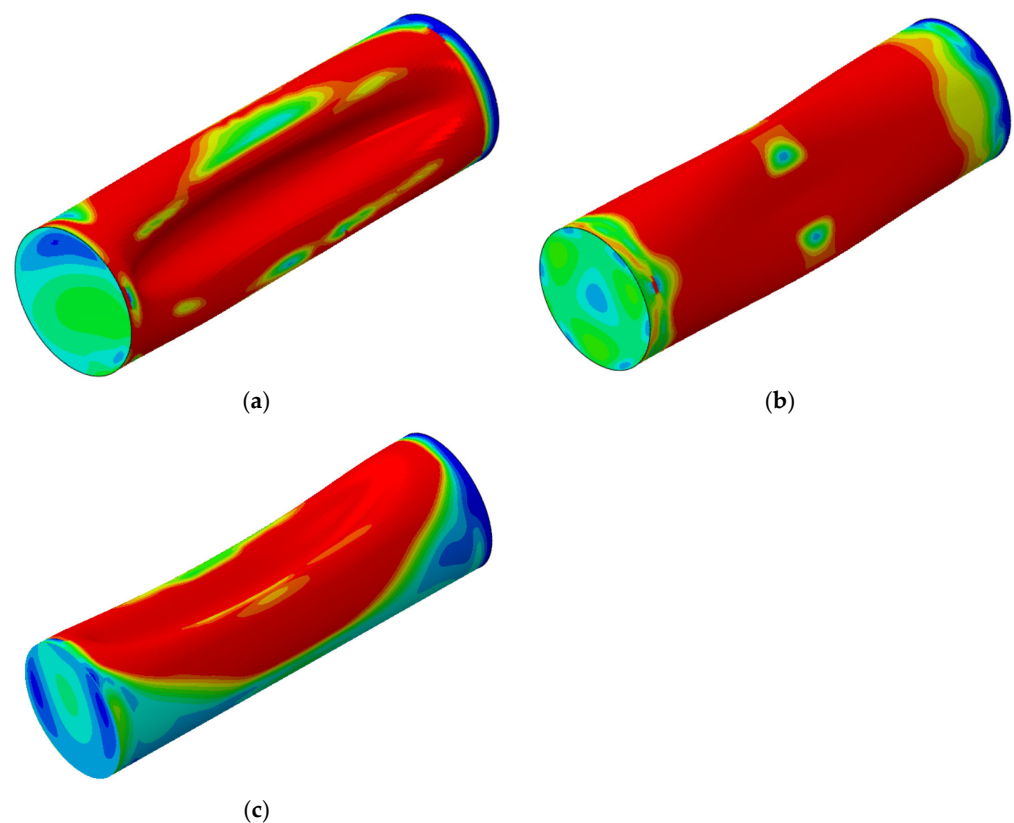


Figure 5. FEM-obtained collapse shapes of selected optimal design candidates from grid search: (a) First ranked candidate model, (b) Second ranked candidate model and (c) Third ranked candidate model. The color contour represents the magnitude of von Mises equivalent stress after the collapse, where red indicates the maximum stress and blue indicates the minimum stress.

It is noted in Table 3 that the DNN prediction is slightly higher than the FEA validation result. This non-conservative error, while small, is a critical consideration for engineering application. This discrepancy is within the 5.02% COV observed between the “ground truth” experimental data and the FEA model itself (see Section 2.2), suggesting it is within the model’s expected error margin. To ensure structural safety and account for the 5.02% COV observed in the baseline FEA model against experimental data, a more rigorous knock-down factor is required. We have updated the factor to $k = 0.90$ (10% margin) to effectively cover the combined uncertainty of the DNN surrogate model and the inherent

scatter in the physical collapse phenomenon, ensuring the optimized design remains safe under marine engineering standards. The constraint would thus be modified to:

$$k \times P_{c, DNN}(L, D, t, \delta_0) \geq P_{c, design} \quad (3)$$

This adjustment formally accounts for the model's error margin and guarantees a conservative design.

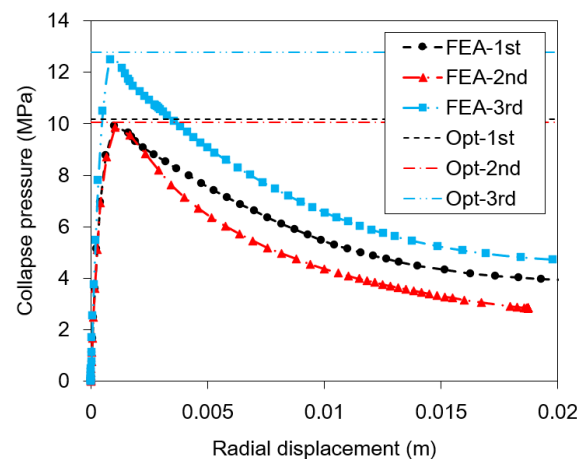


Figure 6. Comparison of collapse pressure versus radial displacement curves between FEA results and DNN model predictions for three selected optimal candidate designs from grid search.

4.5. Computational Efficiency Analysis

The most significant and transformative advantage of the DNN-based framework is its unparalleled computational efficiency when compared to traditional FEA-based design approaches. This efficiency drastically accelerates the design cycle, enabling comprehensive exploration and rapid iteration that are otherwise impossible.

To provide a verifiable benchmark, the computational performance was evaluated on a workstation equipped with an Intel Core i9-12900K CPU and 64 GB of RAM. Under this environment, the performance gains were quantified as follows:

- **FEA vs. DNN prediction time:** A single nonlinear FEA simulation for the collapse analysis of a cylindrical shell typically required 15–20 min. In stark contrast, a single prediction from the trained DNN model was completed in less than 0.05 s. This represents a speed-up factor of approximately 20,000 to 24,000 times for an individual evaluation.
- **Total optimization time:** A traditional FEA-based optimization necessitating hundreds of iterative runs could realistically take days. However, the proposed DNN-based global optimization (setting a maximum of 1000 generations, but practically reaching the convergence criteria within approximately 100 generations) reached convergence in approximately 1.2 s on average (averaged over 10 independent runs). This runtime encompasses the entire optimization loop, including population initialization, mutation, crossover, and constraint feasibility filtering using the pre-loaded DNN model, excluding only the initial library loading time.
- **Grid search performance:** The framework's ability to generate a diverse set of candidates was further highlighted by the grid search tool, which evaluated 10,000 design points in less than 0.5 s.

This drastic reduction in computation time is a critical enabler. It allows engineers to perform significantly more extensive design explorations and detailed sensitivity analyses across a wider parameter space. This capability transforms the design process from a

bottlenecked task into a rapid, interactive cycle, leading to the identification of more robust and weight-optimized designs in a substantially shorter timeframe.

5. Limitations and Future Work

While this framework provides significant advancement, the authors acknowledge several limitations, which will also guide future research.

- **Material specificity:** The current DNN model is strictly specific to the AL-6061 used in the training data, as material properties were not explicit input features. Designers are cautioned that extrapolation beyond the validated material properties or geometric ratios ($2 \leq L/D \leq 15$ and $20 \leq D/t \leq 150$) may significantly increase error rates. For designs involving other materials like HY-80 or titanium, the surrogate model must be retrained with the corresponding material data. The results are therefore material-dependent. Future work should expand the dataset to include various common marine materials (different grades of steel, composites) by adding material properties as inputs to the DNN.
- **Scope of geometry and loading:** The model is validated only for unstiffened cylinders within the trained geometric ratios ($2 \leq L/D \leq 15$, $20 \leq D/t \leq 150$) and under uniform hydrostatic pressure. Extending this methodology to stiffened cylinders or different loading conditions (e.g., axial compression, bending) is a critical next step.
- **Boundary conditions:** The FEA simulations utilized standardized boundary conditions where one end is clamped and the other is constrained radially but free axially. While these provide a consistent and rigorously validated baseline for our current dataset, we recognize that real-world marine structures—such as submarine hulls with rigid end-caps or hemispherical heads—introduce different rotational constraints that can affect buckling behavior. Our current DNN model captures the fundamental mechanics under these standardized conditions, serving as a high-fidelity preliminary design tool. Future expansions of the surrogate model should incorporate diverse end-connection geometries to further enhance its applicability to detailed structural design.
- **Failure mode transition:** Although the FEA model was elastic–plastic, this study focused on instability-driven collapse. For thicker shells or different materials, failure can transition to a material-driven (plasticity) collapse. Analyzing this transition boundary was outside the current scope but is a valuable area for future investigation.
- **Integration with regulatory codes:** The optimization framework is a general tool. For practical application, the design pressure ($P_{c,design}$) and required safety factors must be derived from relevant regulatory codes, which was not part of this study.

6. Conclusions

This study successfully demonstrated a highly efficient framework for the minimum-weight optimal design of unstiffened cylindrical shells, leveraging a pre-trained DNN model as a high-speed, high-fidelity surrogate for FEA. The methodology, incorporating a robust global optimization algorithm (DE) and a practical grid search tool, was proven to be both accurate and computationally transformative. Optimal designs derived from the framework were rigorously validated via independent FEA, showing excellent agreement with prediction errors of less than 3%, confirming the framework’s fidelity for critical design applications.

The most significant contribution lies in its unparalleled computational efficiency. By reducing optimization times from potential weeks to mere hours, this framework acts as a powerful and reusable digital asset. It enables extensive, rapid design exploration that is fundamentally unfeasible with traditional, slow iterative FEA or overly simplified rule-based methods. Crucially, the reliability and practical applicability of the DNN-based

optimal designs were rigorously validated through independent FEA simulations. These validations consistently demonstrated high accuracy, with minimal discrepancies between DNN predictions and FEA results (e.g., errors of less than 2%). This high degree of agreement unequivocally confirms the framework's fidelity and trustworthiness in critical structural design applications.

Future research will focus on several key aspects. The framework will be extended to more complex geometries, such as stiffened cylinders, which are common in marine structures. Further work will also explore multi-objective optimization (e.g., minimizing weight while maximizing stiffness) and the integration of uncertainty quantification. Finally, investigating the performance of the model with smaller datasets and exploring more advanced neural network architectures (e.g., GNNs) could provide further insights into the efficiency and applicability of machine learning in structural engineering.

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