Proceedings of 15th International Marine Design Conference (IMDC-2024)
June 2-6, 2024
Amsterdam, the Netherlands

Enhancing Hull Form Design for Robust Efficiency: A Data-Enhanced Simulation-Based Design Approach

Yasuo Ichinose[1,*] and Tomoyuki Taniguchi[2]

ABSTRACT

This paper presents a design approach that integrates machine learning techniques with traditional physics-based simulations/models to enhance the ship design process with robust efficiency. While generative machine learning methods, which can directly produce design outputs such as the 3D hull form, have the potential to transform the design strategy, ship design inherently involves a decision-making process that requires consensus among stakeholders based on a foundation in physics-based simulations/models. This paper proposes a practical design strategy that positions physics-based simulations/models at the core of the design process, augmented by data-driven models. The paper first classifies hybrid types of the two models and integrates them into a practical design process. Finally, it demonstrates the effectiveness of the proposed design approach by showcasing the impact of data circulation, which accumulates and reinforces data in day-to-day design operations, on improving design outcomes.

KEY WORDS

Ship Design Methodology, Simulation-Based Design, Data-driven Model, Physics-based Model, Hybrid Model

INTRODUCTION

Until now, the application of machine learning in hull form design has primarily involved using parameters that surrogate the hull form, such as principal dimensions, instead of directly dealing with the detailed 3D hull shapes. However, recent developments have begun to propose methods that handle the detailed 3D shapes directly as design outputs. Khan has proposed a machine learning model that uses a deep convolutional generative model to produce multiple 3D hull shapes from a latent input vector (Khan et al., 2023). Similarly, Ichinose has proposed a surrogate model for viscous Computational Fluid Dynamics (CFD) that uses a Convolutional Neural Network (CNN) to estimate the hull resistance, surface pressure distribution, and wake flow distribution at the propeller plane (Ichinose & Taniguchi, 2022) in real-time on a web browser, following to changes in the hull form (Ichinose & Gaspar, 2023). The significant difference between machine learning methods traditionally presented at naval architecture conferences and those proposed more recently lies not in predicting scalar values such as horsepower, which are one of the evaluation values but not the design products themselves, but in the use of decoder models represented by image-generating AI to handle 2D and 3D data, namely the design outputs themselves, including hull shapes and pressure distributions.

The emergence of data-driven approaches capable of directly outputting design products has been impacting ship design strategies. Erikstad has classified Marine system design methodology at the strategy level into four categories:

[1] Fluids Engineering & Hull Design Department, National Maritime Research Institute, Tokyo, Japan; ORCID: 0000-0003-1566-913X

[2] Structural and Industrial System Engineering Department, National Maritime Research Institute, Tokyo, Japan
* Corresponding Author: ichinose@m.mpat.go.jp

Submitted: 13 February 2024, Revised: 26 April 2024, Accepted: 1 May 2024, Published: 21 May 2024

Conference paper, DOI: https://doi.org/10.59490/imdc.2024.856 e-ISSN: 3050-4864

Optimization, Set-based, System-based, and Configuration-based, as an evolution from conventional design spiral methods (Erikstad & Lagemann, 2022). Each method has its advantages and disadvantages, and the choice among them is significantly influenced by design time constraints dictated by commercial practices. Bulk carriers, tankers, and container ships, which are predominantly built in East Asia, are often designed under strict time constraints due to negotiations with shipowners, making it difficult to move away from Design spiral methods. Papanikolaou, in the HOLISHIP project (Papanikolaou, 2022) aimed at Optimization, is constructing surrogate models for CFD calculations, which have been a bottleneck in multidisciplinary optimization due to their time dominance. Additionally, in adopting a system-based strategy, efforts are being made to optimize the entire process using a fast-responsive simulator known as 1D CFD (Perabo et al., 2020). In hull form design, which addresses the highly nonlinear flow around the hull, fast and accurate surrogate models for CFD are essential for designing environmentally friendly ships. Energy Saving Devices (ESDs), installed either before or after the propeller, are adapted on most ships to reduce the environmental impact of their operations. Viscous CFD calculations are the only way to design ESDs while considering the interaction effects between the hull form and the propeller. Integrated design of a hull form, a propeller, and ESDs can improve propulsive performance by a few percentage points compared to the sequential design method(Ichinose & Tahara, 2019). Aiming to enhance the integrated design of a ship's propulsive performance, accurately modeling time-dominant viscous CFD calculations becomes a key technology for adopting next-generation ship design strategies.

Physics-informed machine learning (ML) is one approach to accelerate time-consuming CFD calculations using ML. Raissi has estimated the flow field around a 2D cylinder by applying the Navier-Stokes equations as the loss function during Neural Network training (Raissi et al., 2018). A significant benefit of Physics-informed machine learning is that it eliminates the need for time-consuming mesh generation, which still requires some expert's techniques. Furthermore, "Physics-informed neural networks can seamlessly integrate multi-fidelity/multi-modality experimental data with various Navier–Stokes formulations for incompressible flows" (Cai et al., 2021). Multi-fidelity CFD, a combination of potential-based and RANS-based CFD, has been developed for hull form optimization to expand the exploration space in designing hull forms(Peri & Campana, 2005). Physics-informed neural networks have the potential to smoothly combine these multi-fidelity physics models, which could significantly alleviate the bottleneck in the overall optimization of ships by integrating one-dimensional and three-dimensional CFD methodologies.

On the other hand, ship design is an integral component of larger engineering projects and necessitates a comprehensive design methodology that accommodates the decision-making process, including achieving consensus among stakeholders. While machine learning models and generative AI can offer significant advantages, one of their notable drawbacks is the potential to produce misleading information. Therefore, to facilitate consensus-building and ensure robust decision-making, it is crucial to strategically combine these models with physics-based simulations. Employing machine learning models in a controlled setting, integrated with reliable simulation techniques, is essential for enhancing the accuracy and reliability of ship design processes.

This study discusses how to integrate data-driven approaches with physical model simulation design from a practical perspective. After organizing the structural challenges of current Simulation-Based Design, this paper proposes a practical data-driven method that integrates traditional simulation design with a data-enhanced, rationale-based design approach to overcome these challenges. Finally, demonstrating the proposed method shows its effectiveness. The core of our proposed design strategy is the effective circulation of data, which accumulates and is reinforced through day-to-day design operations. This paper partially showcases the impact of this data circulation, providing partial evidence of the efficacy of our approach.

CHALLENGES IN SIMULATION-BASED DESIGN ARCHITECTURE

First, this paper discuss about challenges in the conventional Physics-Simulation-Based Design architecture. The design of hull form has benefited from the adoption of Simulation-Based Design since around the year 2000 (ex. Matsumura & Ura, 1997). This led to have reduced the number of model tests and contributing to the reduction of design costs. Moreover, flow field information such as the pressure distribution on the hull surface and the wave height distribution provided by CFD outputs has deepened researchers' and designers' understanding of physical phenomena. However, the current architecture of Simulation-Based Design is described as a closed system that combines performance evaluation tools, shape deformation tools, and optimization tools (Tahara et al., 2003). Nevertheless, this architecture has the following practical challenges:

1. Limited Design Space: The time-consuming CFD forces to constrain the design space to exploration in the optimization process.
2. Lack of Information for Robust Efficiency: Decision-making suffers due to a lack of information during the design process.
3. Lack of Design Reusability: Designs can't be reused for similar projects.

Figure 1 illustrates the configuration of the Simulation-Based Design (SBD) architecture and its three challenges. The SBD architecture consists of three components: a Performance Evaluator, which estimates performance using methods such as CFD; a Geometry Manipulator, which performs shape modifications; and an Optimizer, which optimizes these components. This study proceeds with discussions based on this architecture.

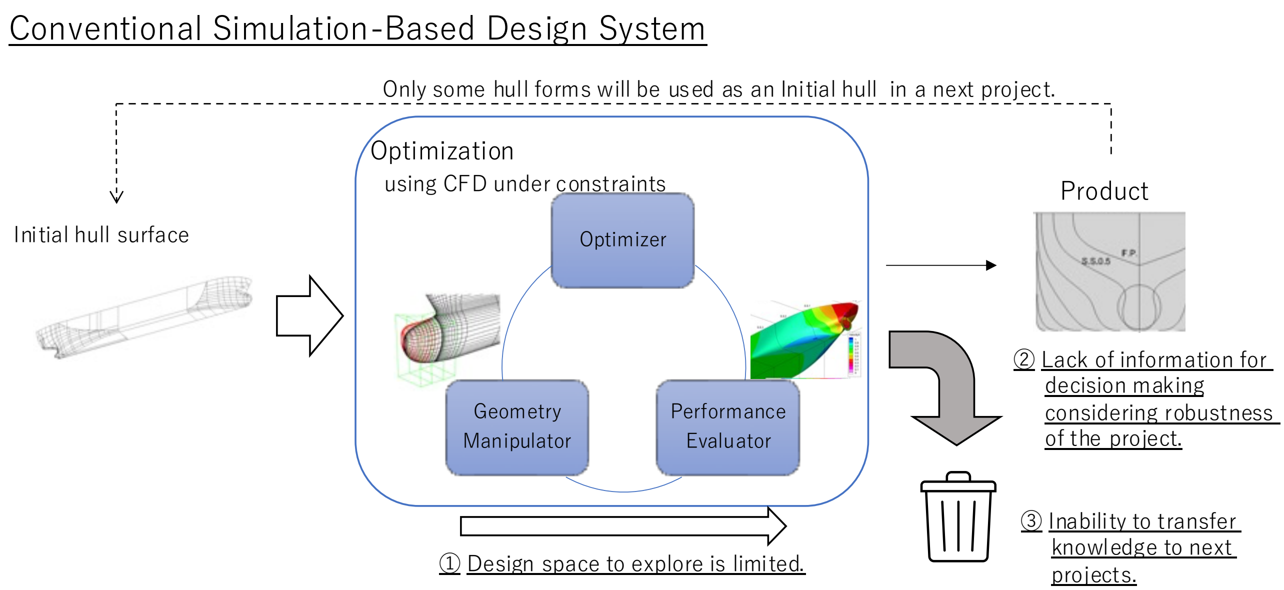

Figure 1: Challenges of Conventional Simulation-Based Design System.

The first challenge in conventional SBD architecture is that time-consuming CFD calculations, especially those solving the Reynolds-averaged Navier-Stokes (RaNS) equations through direct discretization, restrict the design space that can be explored. As a result, a broader exploration beyond basic hull parameters is often left to the designer's tacit knowledge, not covered by the design system. To address this issue, Kandasamy has proposed a method to explore a wider space by combining potential flow calculations with RaNS-based CFD in a multi-fidelity optimization approach (Kandasamy et al., 2010). Furthermore, Diez have suggested a method for dimensionality reduction of the design space through eigenvalue analysis of hull form deformation parameters (Diez et al., 2015). Indeed, these methods accelerate CFD calculations. However, they do not address the challenges of high-dimensional spaces encountered with the parametric hull form deformation methods currently used as Geometry Manipulators. As a solution to these high-dimensional challenges, Ichinose has proposed the use of machine learning to analyze a hull form database through the Hull-form Coordination System (Ichinose, 2022).

The second challenge is that the output of the SBD system is insufficient for design decisions such as determining the hull form, which is the main objective of ship design. The system lacks integration of information on simulation uncertainties, as well as information on other evaluative factors affecting the hull form that are not related to simulation, such as stability, structure, productivity, and propulsive performance. Factors like CFD calculations, scale effects of actual ships, and wave conditions have high uncertainties not currently considered in the SBD architecture. To address this, Tahara have proposed a method that theoretically handles variations in sea conditions and other factors using reliability optimization

theory (Tahara et al., 2014) . Meanwhile, Ichinose and others have suggested visualization of the design space, which is compatible with data-driven approaches (Ichinose, 2022).
The third challenge is the lack of a mechanism within the SBD architecture to reuse data obtained from SBD in subsequent projects, necessitating almost starting from scratch for each redesign. This issue stems from the absence of an information feedback mechanism within the architecture, suggesting that a solution could potentially be found through Data-driven approaches.

FOUR HYBRID MODELING APPROACHES COMBINING PHYSICS-BASED MODEL/SIMULATION AND DATA-DRIVEN MODEL

In ship design, the integration of physical simulations and data-driven methods is not actually a new concept. Ship design has long utilized design charts and empirical formulas from past data as data-driven tools. The direction of integrating physical simulation and data-driven approaches in this study involves replacing these design charts with machine learning models that are more accurate or advanced, and these models will be combined with physical simulations. Especially, the physical explain ability and reliability of the final design outputs based on physical simulations are particularly important considerations. On the other hand, introducing machine learning requires building mechanisms different from before. These include methods of databasing and data visualization, which become new considerations necessary for handling large-scale data.

Kanazawa has classified the enhancement methods of a ship dynamic model for ship motion prediction into four modes (update mode, convert mode, serial mode, parallel mode) while using a physics-based model as the foundation model to ensure physical explain ability and reliability (Kanazawa, 2023). These classifications, which include methods of correcting physics-based simulations and ways of applying machine learning loss functions, aim to increase the reliability of physics-based simulation results.

Moreover, design is a series of processes, and the integration methods of data-driven models with physics-based simulations are not solely for the purpose of improving reliability. That is, in the challenge of how to efficiently and robustly explore the design space to produce the optimal design output, several integration methods of data-driven models and physics-based simulations can be considered.

This study classifies and discusses the integration relationship between physics-based models and simulations and data-driven models in the ship form design process into four models, as shown in Figure 2.

A) Surrogate Model: The purpose of this model is to speed up time-consuming physics-based simulations. This integration method is particularly effective in multi-disciplinary optimization for overall optimization across various fields.
B) Complementary Model: This model is used in the process of narrowing down the design space. Currently, the design space is narrowed down using design databases and design charts based on key hull parameters, and detailed shape design is performed within this narrowed range using physics-based models such as physics-based simulations and model tests.
C) Correction Model: This model corrects the results of simulations or model tests using a design database. It is the most commonly used method in engineering, including scale effect correction of model test results for actual ships and data assimilation.
D) Constrained Model: This model involves setting design conditions and operational scenarios from operational data and designing with physics-based models. In the aviation field, Kim has proposed a model where machine learning models based on flight data set the simulation's flight phases and constraints(Kim et al., 2022).

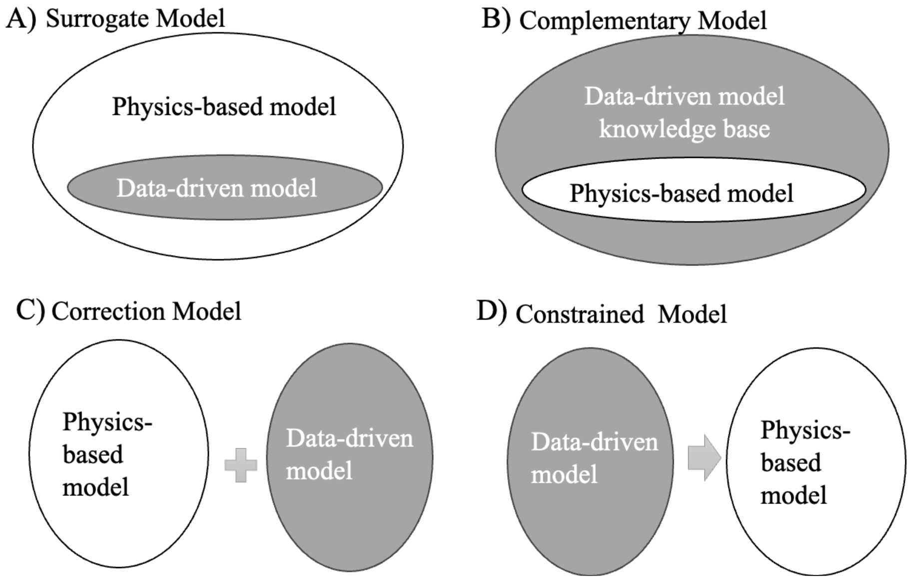

Figure 2: Schematic Representations of Four Hybrid Modeling Approaches Combining Physics-Based Model/Simulation and Data-driven Model

The hybrid models of physics-based models/simulations and data-driven models in the design process can be organized into four categories. However, as these hybrid models are incorporated into the design process, there may be instances where each model is sequentially combined or nested in accordance with the level of detail in the design deliberations. Therefore, when integrating physics-based models and simulations with data-driven models throughout the entire hull design process, it is necessary to appropriately apply these four models to each area of the design process. The next section will discuss how to practically construct a process that integrates physics-based models/simulations with data-driven models.

DATA-ENHANCED SBD ARCHITECTURE

This section discusses how to practically implement the hybrid models explained in the previous section into a practical design process.

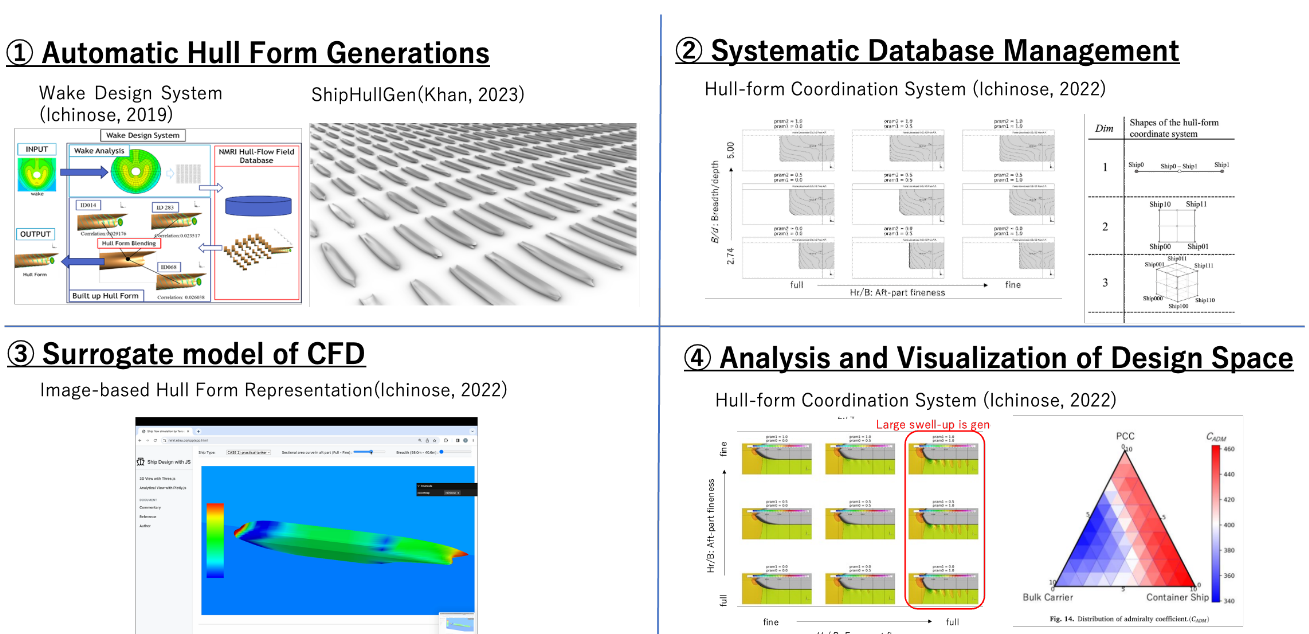

Figure 3: Component Technologies for Integration into Data-Enhanced Simulation-Based Design.

Figure 3 shows four data-driven design technologies that are considered capable of overcoming the challenges of the traditional Simulation-Based Design architecture discussed in the previous section. The first is an automatic hull-form generation tool. A hull design tool that automatically generates multiple design candidates from latent vectors (Khan et al., 2023) or past linear databases (Ichinose & Tahara, 2019) is one of the most critical technologies in the hull design process utilizing data-driven methods. Many conventional formulaic hull representations and parametric hull deformation methods are used for local hull modifications, but not extensively for entire design processes. This is because it is challenging to encapsulate the tacit knowledge of past designs, an asset of shipyards or experienced designers, into formulaic or parametric expressions with limited hull parameters. The second method, the Hull-form Coordination System (Ichinose, 2022), has potential to overcome this difficulty. It uses assets of past design project as basis vectors, allowing systematic expansion (interpolation) of hull form which was unable to express in conventional formulation. The purpose of interpolating hull form to increase database density is to create a CFD Surrogate model. For example, expanding the database with the Hull-form Coordination System by dividing 15 basic hull forms into four parts can automatically generate 15,504 ($={}_{15+(4+1)}C_{15}$) hull forms. With a system that constantly runs CFD calculations in the background for these hull forms, the database and CFD Surrogate model (Ichinose & Taniguchi, 2022) continuously update based on accumulating day-to-day design work. Naturally, this database can also include data generated by traditional parametric hull representations and deformation methods. The last of the four is the method for analyzing and visualizing the database. Nonlinear optimization methods for designing hull forms within specific constraints often result in local optimal designs with uncertainties questioning their robustness. This necessitates further investigation by designers before deciding on the final design of a ship. The method for analyzing and visualizing the database enhances the robustness of these designs by allowing for analysis and visualization of the design space surrounding the optimal solution.

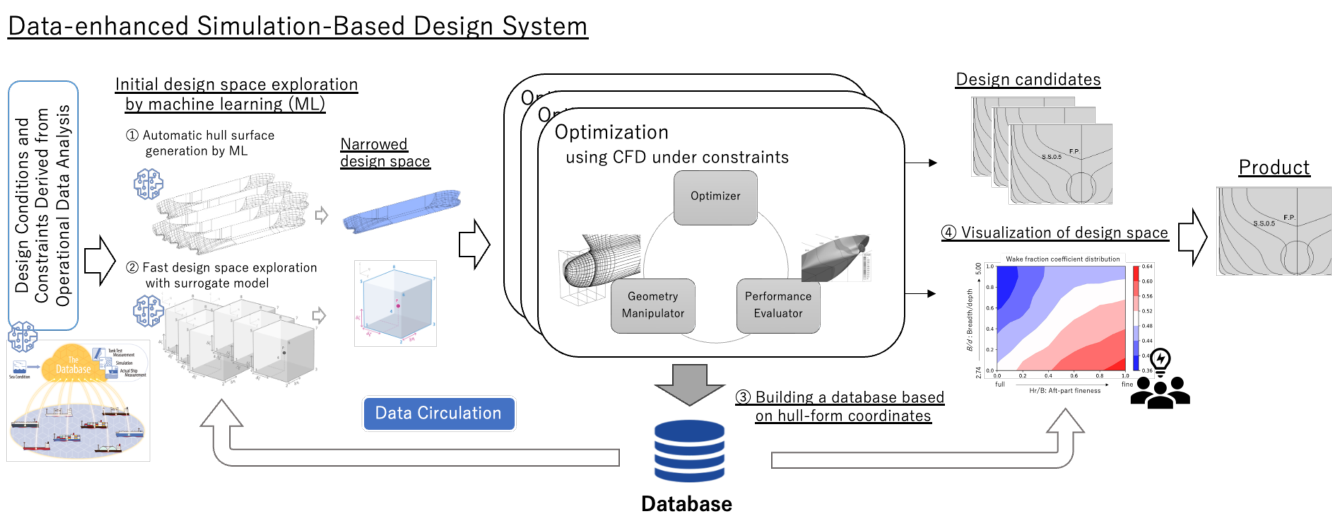

Figure 4: Overview of Data-Enhanced Simulation-Based Design system.

Considering the ways of integrating models discussed in the previous sections, this paper proposes the Data-enhanced Simulation-Based Design method illustrated in Figure 4. Here, based on the observation that the decision-making of the design process is always carried out based on physics-based model and simulation such as CFD and towing tank tests, the term "Data-enhanced" is used to explicitly denote the enhancement of processes using data, signifying the symbiotic relationship between data-driven methods and physics-based simulation.

As shown in Figure 4, the foundational Simulation-Based Design architecture is incorporated within the proposed method, enveloping it with the application of hull form databases and machine learning methods to overcome the three challenges of traditional SBD. First, regarding challenge 1 – limitation of the design space, the proposed method features initial hull form recommendations using the hull form database (1 in Figure 1) and narrowing down the design space with a CFD calculation Surrogate model by machine learning (2 in Figure 1). Next, for challenge 2, the proposed method addresses this challenge through two methods: proposing robust hull form selection using the Visualization method of the design space shown in 4 in Figure 4 (Ichinose, 2022), and multi-objective optimization considering general arrangement, stability, structure, and productivity (Papanikolaou, 2022). Lastly, for challenge 3, the proposed method enables data reuse in similar projects by creating a database of all CFD calculation results and hull information, including performance evaluation results of hull forms discarded during optimization calculations, by databasing them based on the Hull-form Coordinate System treating each hull shape like a gene, thereby creating a cycle of data.

DEMONSTRATION OF THE PROPOSED METHOD

This section demonstrates the effectiveness of the proposed Data-enriched Simulation-Based Design method through a partial demonstration.

This paper takes as an example the design database shown in Table 1, which simulates an asset in a shipyard. Generally, shipyards tend to build ships with similar principal dimensions which they have built in the past, due to factors like crane capacity and dock size. The designs of these previously built ships are saved as CAD data along with CFD calculation data. These data have not been able to be organized by a set of hull parameters, making it difficult to database them. The Image-based Hull Form Representation method (Ichinose & Taniguchi, 2022) holds the hull form as the surface data of CFD structural grids, saving this data in a format similar to image data, which is more manageable for machine learning methods, thus allowing for databasing. This makes it possible to database nearly all hull forms that can be represented by structural grids.

Furthermore, the Hull-form Coordination System can generate new hull forms from this database. This method allows for the automatic expansion of a denser hull form database suitable for machine learning. The 20,952 data points shown in Table 1 are from a hull form database expanded from 20 basis hull forms using the Hull-form Coordination System. This expanded database is utilized as a surrogate model for CFD calculations by a Convolutional Neural Network (CNN) model.

Table 1: Overview of Database for the Demonstration

Ship Type	Container Ship, Pure Car Carrier, Bulk Carrier, Chemical Tanker, Oil Tanker, Mathematical Hull Form with Buttock Flow Stern
Basis Ships	20
Total Number of Ships	20,952
Length/Breadth	5.00 – 7.50
Breadth/Draft	2.0 – 3.60
Blockage Coefficient	0.47 – 0.88

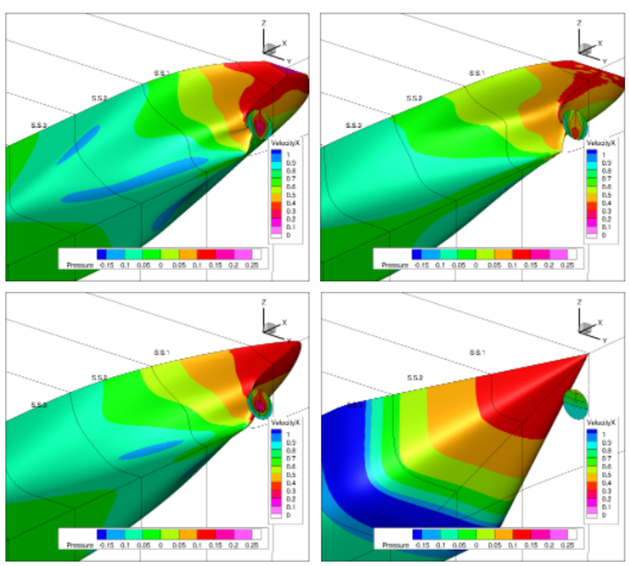

Figure 5: An Examples of Hull Forms and on the Database generated by Basic Ships

A feature of this proposed method is that the items related to estimated propulsive performance are not limited to integrated values such as resistance values, which have traditionally been estimated by design charts. By incorporating a Decoder model into the Neural Network architecture, as shown in Figure 6, it is possible to present information useful for designers to understand physical background and deepen the insight, such as the pressure field on the hull surface and the wake flow distribution on the propeller surface. The Decoder model is a type of generative AI model used for creating images. Historically, the application of machine learning in ship design has been confined to tasks such as classification and scalar value inference. While scalar values, such as main engine output, are essential estimations for design, they do not provide guidance on which specific parts of the hull form could be improved. In contrast, models utilizing the Decoder model can estimate the pressure distribution on the hull surface and the wake distribution behind the propeller. This capability marks a significant shift as it offers detailed guidelines on how to modify the hull form for design improvements, providing much-needed directional insights for enhancing overall ship design.

Moreover, the estimation time for this surrogate model by machine learning is less than 0.1 seconds, significantly faster than the hours it takes for one case of RaNS-based CFD. Although the design space that can be covered by machine learning is limited in this example, in actual operation in shipyards, it is assumed that the design exploration range of this surrogate model is almost equivalent to the entire expected design space due to the abundance of conventional databases and the ability to semi-automatically construct a large amount of hull form data using Hull Form blending methods or FFD methods.

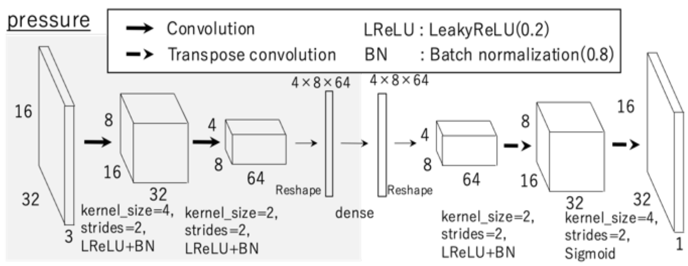

Figure 6: Architecture of neural network for prediction of pressure distribution

Figure 7 shows the difference between the resistance coefficient predicted by the CNN model and the true value (CFD calculation value). The dataset shown has not been used in the machine learning training. The results in Figure 7 confirms that the resistance values are estimated within $\pm 5\%$ accuracy that is sufficient for practical design across a wide range of ship types and principal dimensions. This estimation is intended for narrowing down options in the preliminary phase of traditional design.

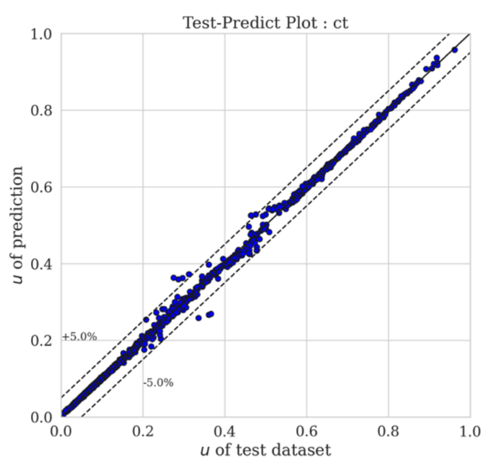

Figure 7: Comparison of prediction and grand truth of resistance coefficient

Next, Figure 8 compares the predicted and true values of the pressure distribution on the hull surface by the CNN model. The figure shows the pressure distribution from the bow to the stern from left to right, and from the bottom to the water surface in the girth direction from bottom to top, accurately reproducing the island-like shape of the pressure distribution that creates the adverse pressure gradient significant for resistance at the stern bilge. Such information is necessary for designers to physically understand why resistance has increased. Even while using an estimation method that can easily become a "black box" like machine learning, providing a means to understand physical phenomena is one advantage of the proposed method.

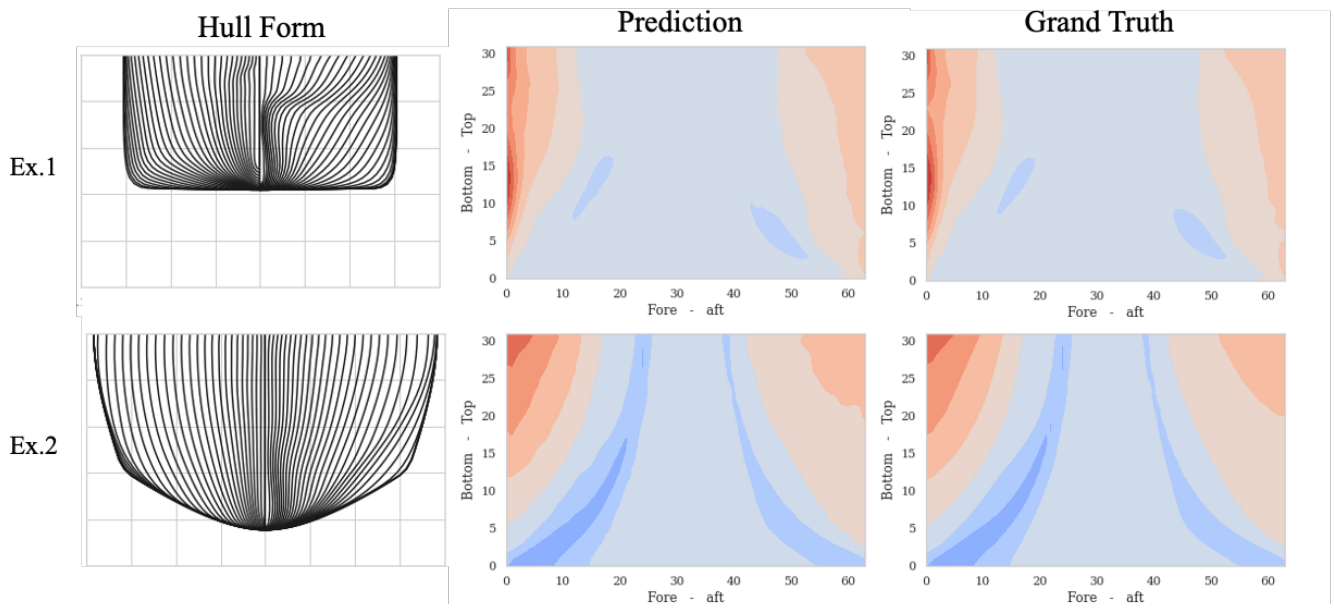

Figure 8: Comparison of prediction and grand truth in pressure prediction

CONCLUSIONS

In conclusion, this paper has explored the transformative potential of machine learning techniques for directly producing design outputs, such as the 3D shape and pressure distribution of hull forms, within the realm of ship design. However, it also underscores the critical importance of achieving consensus among stakeholders in the inherently complex decision-making process of ship design, a process deeply rooted in physics-based simulations/models. This paper proposes a design strategy that leverages the strengths of both physics-based and data-driven models, positioning the former at the core of the design process while enhancing it with the latter.

This paper has systematically outlined a method for hybridizing two model types and demonstrated their effective integration into a practical design process. This approach not only adheres to the traditional reliance on physics-based models but also leverages the efficiency gains provided by machine learning. The demonstration confirms that the CNN model, serving as a tool for initial exploration across a wide design space, can predict resistance performance with an accuracy of ±5%, which is sufficient for practical design across a broad range of ship types and principal dimensions. Additionally, this machine learning model is capable of estimating pressure distribution in viscous flow with high Reynolds number within 1 second, thereby enabling designers to incorporate physics-based insights to achieve robust efficiency.

CONTRIBUTION STATEMENT

Yasuo Ichinose: Conceptualization; data curation, investigation; methodology; software, validation; visualization; writing – original draft. **Tomoyuki Taniguchi:** Formal analysis; software; writing – review and editing.

ACKNOWLEDGEMENTS

This work was partially supported by JSPS KAKENHI Grant Number 20K04954.

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