Interactive ship flow simulation enhanced by neural network model in a web environment

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ABSTRACT

Hydrodynamic simulation of marine structures is a complex and time-consuming task that requires large, refined models to accurately estimate the behavior of ships. During the conceptual phase, therefore, these estimations may be more efficient if done with a mix of surrogate models and simplified simulations. We believe that AI and the web environment can contribute to providing a more precise answer and fast solution, especially when the design domain can be narrowed and properly estimated. This paper shows an attempt in this direction, describing a web-based real-time flow simulator that is composed of a Tenforflow.js-based convolutional neural network model with an image-based hull form representation. Some case studies demonstrate the advantages of a novel web-based prototyping environment in the conceptual and initial design of ships. The image-based hull form representation method with a convolutional neural network enables the design of not only main dimensions but also local shapes in an interactive web-based concurrent engineering environment. Our approach extends the neural network model of wake flow estimation to models of the prediction of resistance and pressure distributions on the hull surface and develops a novel web-based prototyping environment for the conceptual and initial design of ships.

THE PROBLEM OF DEMANDING HYDRODYNAMIC SIMULATIONS IN MARINE ENGINEERING

Design for the marine environment is a collaborative process that involves multiple disciplines, summarized by Andrews (2018) as the S^5: stability, speed (propulsion), structure, seakeeping and style. A software system can modularize and classify individual disciplines as a separated analyses; nevertheless, a designer must later integrate multiple solutions into a *whole ship model* (Calleya *et al.*, 2016). This *true-model,* shared among key stakeholders, is provided in a series of 3D/2D models, as well as CAD/CAE results, with different level of fidelity according to the lifecycle phase of the design (Gaspar, 2019).

One bottleneck in this iterative process is the hydrodynamic assessment of the hull, exemplified in the rest of this article by the case of the flow simulation around the ship and propeller. Such analyses are paramount to determine important ship performance indicators, such as selection of the propulsion system, fuel consumption and seakeeping. This calculation is usually time-demanding, based on Reynolds-averaged Navier-Stokes (RaNS-based) Computational Fluid Dynamics (CFD) methods. Specially during early stages of design, such time-demanding analyses may hinder the realization of multidisciplinary optimization and concurrent engineering. Therefore, dependeing on the stage that a project is, it may wise to introduce multi-fidelity models, including surrogate models. Modern methods goes one level up above the traditional *regression tables* from the previous decades, using now machine learning (Ichinose, 2022). This is crucial for substantially reducing design time and expanding the explorable design space.

The main objective of this paper is to combine modern approaches to tackle accurate hydrodynamic simulations, such as the work from Ichinose (2022) in a interactive and responsive web-environment, previously discussed by Fonseca and Gaspar (2019) and Gaspar (2017). We developed a web-based real-time flow simulator to realize concurrent engineering in the conceptual and initial design stages by surrogating the time-consuming RaNS-based CFD calculation with a convolutional neural network (CNN) model that is based on Tenforflow.js. This surrogate model not only enables the prediction of propulsive performance, which is an update to the standard design chart or regression formula, but it also enables the prediction of pressure distribution on hull surfaces and wake flow behind the ship, which is essential for propeller design.

A PRAISE FOR WEB-BASED SIMULATION

Fonseca and Gaspar (2019) summarizes, at the 33rd ECMS, the advantages of a web-based environment. It gives advantages regarding sharing, compatibility, open source development and interactivity of engineering simulations. The fact that it is possible to share web simulations with anyone who has access to an internet connection, without the need of installing new software, check licenses or configuring a server, makes the approach convenient to give distributed users access to

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the same model. This centralization also allows unified support of the application, as once the developer deploys a new version of the source code online, all users instantly obtain access to it.

Moreover, compared to traditional engineering programming environments, web technologies provide more options and freedom for the creation of sophisticated user interfaces. The developer of a web application may use sliders, text fields and buttons to gather inputs from the user. Results can be presented as formatted text, tables, plots or interactive visualizations, either 2D or 3D. By changing the CSS, the same code can be used for desktop, mobile (app) or tablet. Multiple textual and graphic elements can be combined in dashboards to present a cohesive experience to the user, allowing them to vary inputs and observe the effects of the variation on the results in real-time.

Using JavaScript as main pillar (Gaspar, 2017) allows the extensive use of available open libraries, e.g., for solution of mathematical models, creation of 2D plots and rendering of 3D scenes. As this is aimed at the human user, interactive GUIs is a key point, allowing the simulations to convey meaning easily to users, including those who do not have an engineering background.

The technology is backed by the big tech-companies, and nowadays JavaScript runs fast. A regular consumer laptop, or even a smartphone, is capable of executing the applications in real-time, solving the mathematical models and rendering the 3D scenes. Given the scope of the examples observed in Gaspar (2018; 2022), this includes simultaneous solution of differential equations, manipulation of 3D geometries and rendering of textures in the web browser. For such reasons, it becomes apparent that the approach is usefull, while still provides unexplored potential for further work. In this sense, we plan to explore the inclusion of neural networks (NN) via TensorFlow (https://www.tensorflow.org/), combined to existing optimization work towards more efficient hydrodynamic simnulation from Ichiniose (2022).

FLOW PREDICTION BASED ON A CONVOLUTIONAL NEURAL NETWORK

The hydrodynamic example here used to proof the concept is the flow prediction of a ship, based on a convolutional neural network.

The flow simulation for ship design can be broken down into simulations of waves, propellers, and viscous flows. Of these three, the wave and propeller simulations are not much of an impediment to integrated design since they can be estimated with good accuracy using potential theory, which can be computed in a few minutes. On the other hand, a viscous flow simulation takes more than a few hours, because it should solves the nonlinear equation of Reynolds-averaged Navier-Stokes (RaNS) and the flow simulation with a high Reynolds number (actual ship $10^{8\text{-}9}$, model ship: $10^{5\text{-}7}$) necessitates detecting complex flow characteristics in a very thin surface layer on the hull. This causes drastically increasing the grid size. Moreover, contrary to wave simulation, viscous simulation should consider the interference effects of hull form and propeller shape. The interaction between the propeller and the flow field generated by the hull, known as the *wake field*, increased the propeller's performance by about 20%, allowing the propeller to be installed at the back of the ship (Carlton, 2007). This interaction has a significant impact on fuel consumption and vibration, both of which are important factors in ship performance. In addition, despite the design for wave-making, the design for viscous flow should be accomplished in collaboration between a hull form designer in a shipbuilding company and a propeller designer in an equipment manufacturing company. Therefore, the viscous simulation of wake fields is one of

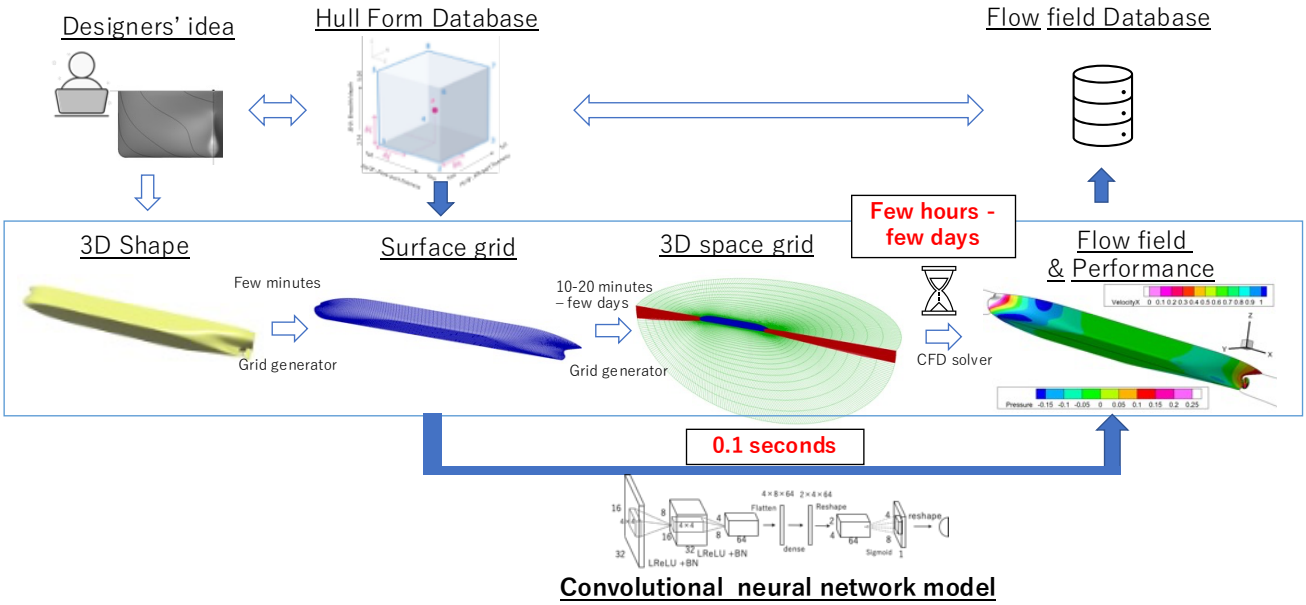


Figure 1: Comparison of data flow between conventinal CFD analysis and convolutional NN model prediction

the root causes of stacking the entire ship design process, is the bottleneck of the expansion of the explorable design space, and hinders multidisciplinary optimization within the S^5.

Figure 1 illustrates the conventional framework of CFD calculation and proposes a neural network model as an alternative. Given that a three-dimensional surface has theoretically infinite shape parameters, it is difficult to generate a hull form automatically; therefore, each hull form is created by hand using CAD by a team of experts. Experts continue to create the hull shape and evaluate it using time-intensive CFD until the hull reaches the desired level. In this process, the conventional design system dismisses these candidates as unqualified for a design restriction, but they have the potential to be qualified hulls in another design condition and to be composed hulls from a database containing design knowledge from experts.

The proposed system collects these legacy assets and employs them to construct a CFD surrogate model. In addition, the database of hull forms can be automatically expanded by the hull form blending method, which can generate a new hull form by morphing multiple hull forms, as proposed by Ichinose (2022) and Kim *et al.* (2019) . The surrogate model of a neural network is intended to be trained by these shipbuilding company or design firm assets. A shipbuilding company's surrogate model enables fast and accurate simulation of similar ship variations, which may be the most common of all design patterns in a particular shipyard due to the facility's limitations in terms of ship sizes and types. Even if a yard wants to design a novel ship type that is not in its database, a dataset and trained model from another ship yard or design farm could be traded, creating a new market for the transaction of design knowledge that is typically discarded during the design process.

Ichinose (2022) proposed a CNN model for wake field prediction that, when the NN training is done, can be up to 10^5 times faster prediction than the RaNS solver with similar accuracy. To realize this prediction model, it was used an image-based hull form representation (IHR) method for representing three-dimensional curved surfaces that is suitable for machine learning, where a 3D hull is transformed into a RGB image. The idea behind the representation is to map a three-dimensional surface to two-dimensional structured data with (x, y, and z) values using a structured grid surface. This data can be translated into the same structure as image data, which is expressed by three primary colors on the vertical and horizontal pixels (cyan, magenta, and yellow). This method has significantly enhanced the quality of shape representation in artificial neural networks.

Traditionally, design charts, empirical regression formulas, or in-house hull shape criteria are employed in the initial design stage to predict propulsion performance. Since parametrization of complex three-dimensional surface shapes is challenging, hull forms are represented by limited shape parameters with few parameters, such as dimensions or shape coefficients, which hinders the high-resolution consideration of local shapes and holistic design. The IHR and proposal prediction methods enable the capture of an entire form with high resolution by handling three-dimensional surface shapes with more than a few thousand parameters. This high-resolution illustration also fits very well modern NN models, as many of them are designed to receive an image as input.

In addition, whereas the design chart or empirical regulation formula generates only a scalar value of the results in prediction, such as the resistance coefficient, the proposed method can generate not only a scalar value but also a pressure distribution or flow field, which is enabled by the generative network architects of the present neural network. This significant advantage has a substantial impact on the design of other fields. The flow field, for example, can be used as a detailed and specific design condition for propeller design, and structural engineers can use the distribution of forces on the hull as a key input for structural design.

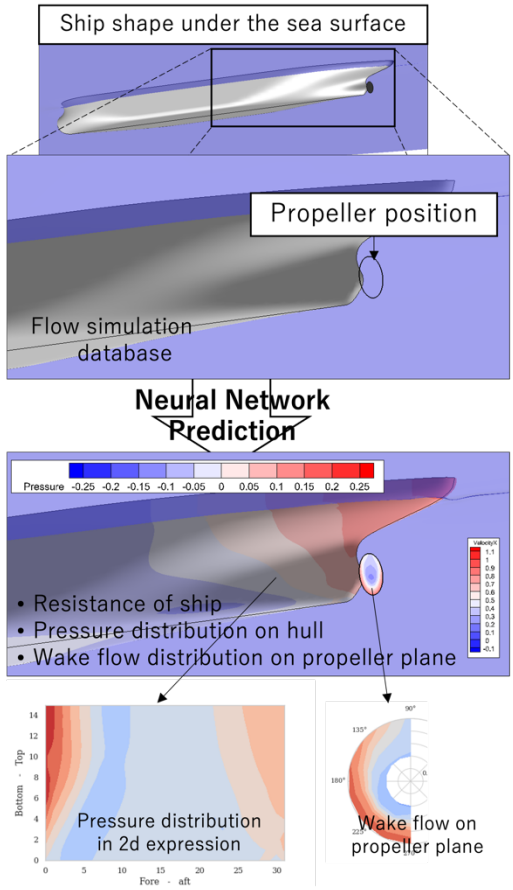


Figure 2: Overview of a surrogate model of ship flow simulation by CNN.

Our work here extends the IHR-CNN method from the estimation of wake flow to the prediction of resistance and pressure distributions on the hull surface, as shown in Figure 2. The architectures of the proposed models for predicting wake flow field, pressure distribution and

resistance are depicted in Figures 3, 4, and 5, respectively, all based on Ichinose (2022). All models have identical encoder parts, which are indicated with a gray background and are used to detect hull form information. The decoder parts are modeled using the DCGAN network (Radford *et al.*, 2016).

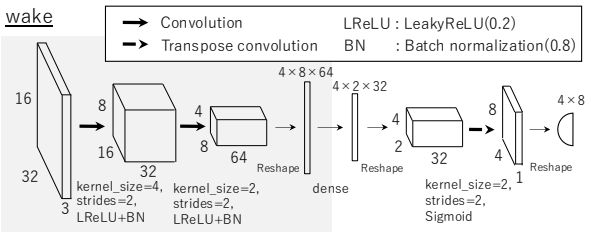


Figure 3: Architecture of neural network for prediction of wake distribution (Ichinose, 2022).

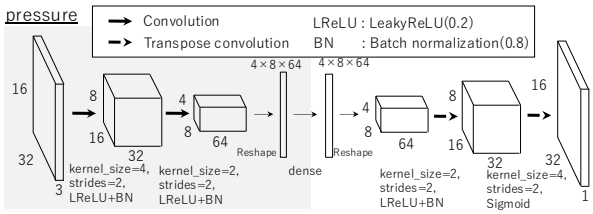


Figure 4: Architecture of neural network for prediction of pressure distribution.

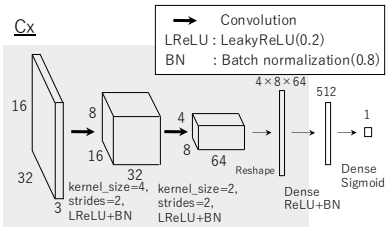


Figure 5: Architecture of neural network for prediction of resistance coefficient (*Cx*).

The loss function for the training is mean square errors of each of the flow velocity, the surface pressure, and resistance value, respectively. As the solver of optimization to reduce the loss function in the training, Adam method is applied in traing of all models.

Tensorflow, wrapped by Keras in a Python environment, is used to build and train the convolutional neural network model on the powerful GPU machine in our facility. The trained model is exported as a JSON file to the TensorFlow.js in JavaScript environment.

FAST AND INTERACTIVE FLOW PREDICTION – SIMUALTION VIA WEB

Our vision of web-based concurrent engineering expects the realization of a collaborative design environment involving your coworkers, customers, and various stakeholders in the new design discussion. To avoid disrupting a discussion regarding a new design, it is preferable to respond to the simulation result for the new design within a few seconds. Therefore, this paper defines fast as a couple of seconds of simulation response, almost as real-time feedback. To achieve interactivity and responsiveness, we make use of the modern GUI toolset for the web (HTML + CSS + JavaScript; Gaspar, 2017). A great example is the use of *oninput* fuctions in sliders, which leads to a very intuitive way to modify variables, and the real-time update recalculates automatically every plot. It requires no compilation, no run button, no external installation, runs direct from the browser, can be shared online (in a standard configured webserver) or private (with .HTML file and additional libraries). From the user's point of view, it requires almost no explanation when the GUI is made properly – sliders change variables, which changes the simulation and updates the plots.

Figure 6 exemplifies shows the parametrization of a hull is done with two inputs, Sectional area curve in aft part and ship breadth. Each new value on the slider calls a function that updates in real time the 3D plot and wake prediction result (https://nmri.ntnu.co/spp/spp.html).

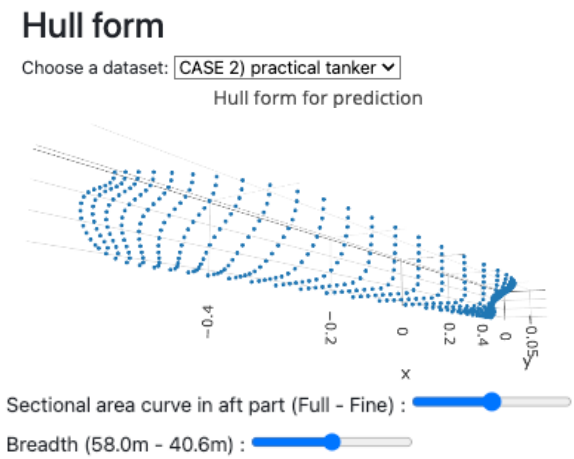


Figure 6: Slides are used to interact with the simulation and explore de thesign space

```
class Hull {
 . Class represent a hull form
 constructor(hullTensor, dataInfo)
    . Construct Hull class instance from
      hull data of tensor format
}

function changeHull()
  . READ user manipulated parameters
  . CREATE target hull form based on the
      parameters by blending method.
 return hull

function predict()
    . READ tensorflow.js model from external
      file
    . CALL changeHull()
    . CALL predict in tensorflow.js function
    . PLOT predicted data on screen
```

Figure 7: Pseudocode for the function in each slide.

A pseudo-code representation of the iteration is shown in Figure 7. Prediction is invoked whenever the hull's

parameters update (e.g., when the user chnegs the value of a slide). Tensorflow.js's imposition of code simplifies the code, which contributes to enhanced maintainability and scalability. It efficiently compresses an enormous amount of CFD database into a single model, allowing us to avoid complex database management on the backend. In addition, diverse open-source libraries accelerate the development of our prototypes, such as Plotly.js, which provides fantastic visualization in a simple manner (see Gaspar, 2017 for more).

CASE STUDY AND DISCUSSION

Two case studies are used to demonstrate the advantges of the interactive tool. A simple prismatic barge firstly exemplifies the fundamentals of the system configuration. The second case study, on tanker design, describes a more realistic approach to ship design using the current method.

CASE 1 prismatic barge (parametrized hull form)

Let's start with the straightforward scenario where design space is described by a mathematical expression. Figure 8a depicts the entire process of building a database and machine learning model.

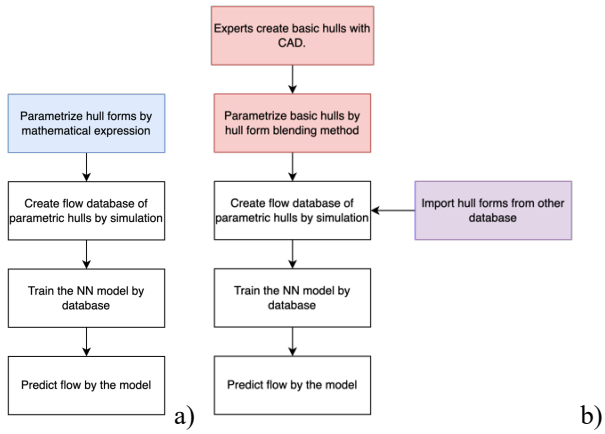


Figure 8: A flow chart of prediction for simple hull forms (a) and for practical hull forms (b).

Several mathematical expressions of the hull have been proposed; we adapt Lewis form for the section form of the hull. The shape of Lewis enables us to manipulate the sectional shape of the hull. As shown in Figure 9, the sectional area is the first parameter of the Lewis form function in this demonstration.

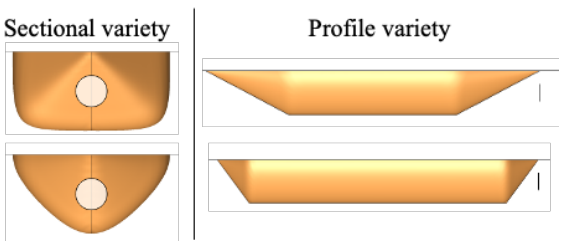


Figure 9: Sectional shapes of Lewis form expression and profile shapes

We also impose control over profile lines, which are the outline of the side shape. The parameterized profile line is depicted as a combination of straight lines. In this demonstration, the second hull form parameter is employed to control the slope angles of the forward and aft part lines.

In building the database, we divided each of the two parameters into 50 divisions that generate 2,601 (=51^2) individual hull forms. All the hull forms is used for simulation of flow field by RaNS CFD code NAGISA (Ohashi *et al.*, 2019).

Figures 10 shows comparisons between the pressure and wake flow predictions made by trained NN models and the truth. The pressure distribution results demonstrate that the proposed model can accurately predict the pressure distribution on the hull surface, which exceeds the level of practical accuracy required for ship design.

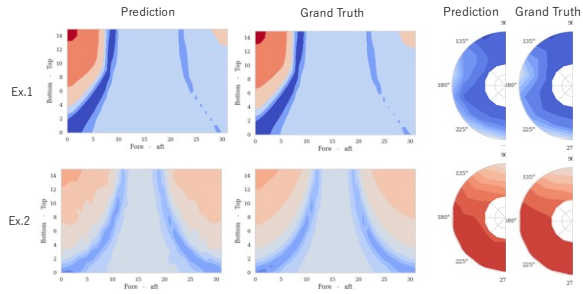


Figure 10: Comparison of prediction and grand truth in pressure prediction and wake for CASE 1.

These predictions are implemented as a JavaScript web application with interactive responses, as shown in Figure 11. Based on the trained model, the Tensorflow.js application predicts the pressure distribution and wake flow field on the propeller plane in real time. This fact proves that the current approach for implementing concurrent engineering in the maritime industry is promising.

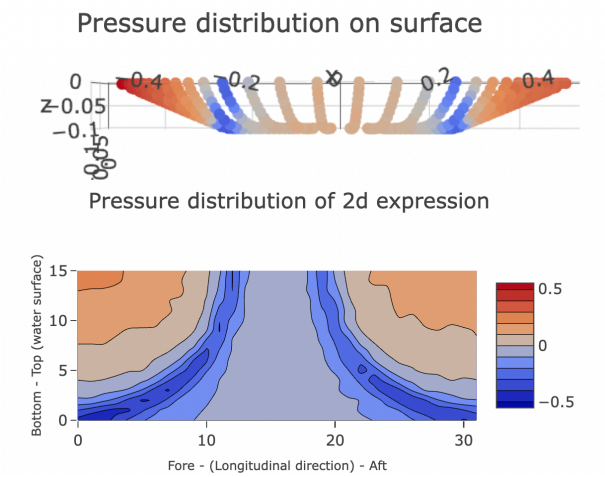


Figure 11: Output from the WebApplication for case 1

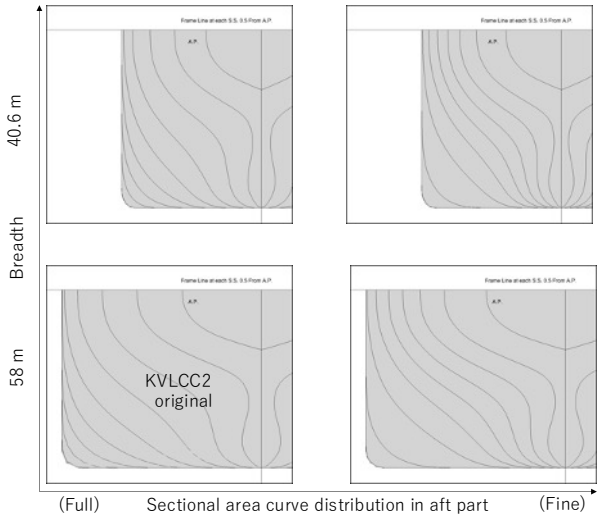
CASE 2) Tanker design (practical design)

Since experts construct their own hull forms using CAD in practical design, it is difficult to parameterize them mathematically. As depicted in Figure 9b, the proposed method can include these expert hull forms directly in the database. On the other hand, there are cases in machine learning training where sufficient data for learning cannot be obtained from the data of these experts alone. In the proposed method, therefore, the hull blending method proposed by Ichinose (2022) is utilized to augment these data.

In case 2, the interactive flow simulation for the practical design is demonstrated using a published hull form of a tanker called KVLCC2 (Van, 1998; SIMMAN, 2008), illustrated in Figure 12.

Figures 12: KVLCC2 model (Van (1998), SIMMAN (2008))

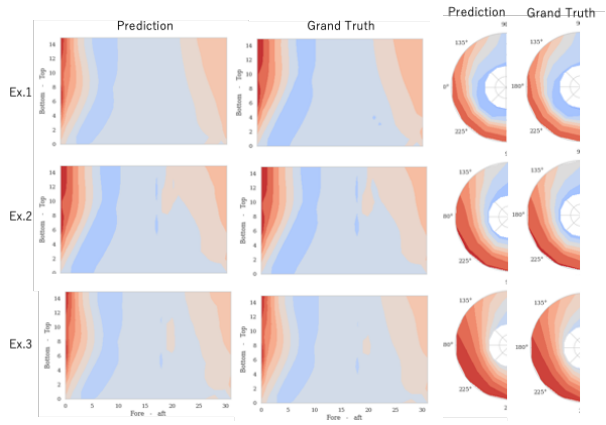
Here, simulating a practical design, it is assumed that the KVLCC2 hull form is used as the initial hull form, and an expert uses CAD to construct four basic hull forms with two design intentions as shown in Figure 13. By using the blending of hull forms proposed by Ichinose (2022), the number of basic hull forms can be any number such as 2, 3, 4, 5, and so on, facilitating the development of a hull database.



Figures 13: VLCC database

The size of the database for study case two is 2,601 designs, which is the same as the size of the domestic-749-gross-tonnaged database that is used for quantative verification of the IHR-CNN method by Ichinose (2022). This database is organized on the 50 divied meshed for the each parameters, in the samemanner as study case one.

The trained neural network model predicts the pressure distribution on hull surface and wake flow at propeller plane as shown in Figure 17. The exploration of the design space is done via the web application, which simulates these complex flows in real time (Figure 18). The user can interact into any variation for Breadth between 40.6m – 58m, as well the fulness of the section area. Resistance coefficient, pressure distribution and wake flow are calculated immediately.



Figures 17: Comparison of prediction and grand truth in pressure prediction and wake flow for case 2.

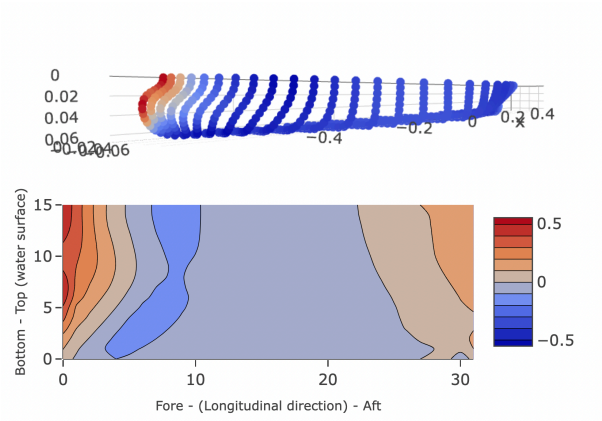


Figure18: Results from the pressure distribution and wake flow calculation in the web-based applicartion.

CONCLUDING REMARKS

This paper presented a web-based interactive real-time flow simulator with a Tenforflow.js-based convolutional neural network model intended to extend the role of the design chart and substitute the time-consuming RaNS-based CFD computation in the conceptual design stage. This surrogate model allowed for the prediction of propulsive performance as well as wake flow behind the ship. The core contribution of this work is the demonstration that, merging complex hydrodynamic simulation using neural networks in a web-based environment, is a reality. The examples here discussed are indeed running online in real-time.

We reiterate that these types of tools are particularly beneficial in the early stages of design, during the exploration of the physical design space. Indeed, there is

an additional effort to prepare the GUI, as well as implement the code in JavaScript. This effort is compensated when the tool is used by multiple stakeholders, as the extra development time shows benefits when users can quickly and efficiently explore the design space, saving time over the whole process. Such examples must be available openly and online, in a similar way to the Vessel.JS library (Gaspar 2018; 2022). This allows peers to build on each other and create a larger library of similar problems, as discussed by Miquel et al. (2020), fostering collaboration in the field. The method also allows for local installations and the handling of IP for commercial use.

Future work includes the incorporation of potential flow and more advanced seakeeping. Our testing suggests that meshes in the order of 10^3 to 10^4 panels can be run online in close to real time, obtaining a result similar to complex simulations from the last two decades.

We finish the paper with a call for our peers to consider implementing open and collaborative web-based methods in the everyday design tasks, both at academic and industrial environments. Simple practices, such as a a Github page for a project – either public or private (paid) is also an experience highly recommended. A core point defended in this paper is that technology is not a bottleneck for complex web-based simulation, exemplified by the current fast- paced stage of online web-development, neither the speed of the computer processors and memory size, but rather how modelling data is able to be transferred from books and experience to useful reusable models. Reusability, even when proprietary, means that a code can be reused internally for the next project and, when public, may be accessed by clients and suppliers.

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(see: https://www.ntnu.edu/ihb/ship-lab)

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