

Investigation of the Erosion Risk and Fluctuating Pressure according to ESD Designs using OpenFOAM

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ABSTRACT

To enhance the fuel efficiency of large commercial vessels, various types of Energy Saving Devices (ESDs) are employed. Among these devices, the duct-type ESD with fins is the most widely used device in shipyards. However, it is crucial to prioritize the consideration of cavitation performance during the design stage of this ESD, as it significantly impacts propeller cavitation.

In this study, the open-source program OpenFOAM was used to investigate the behavior of cavitation, fluctuating pressure and erosion index according to the design variables of the duct-type ESD, called Hi-PSD[®] (HD Hyundai Pre-Swirl Duct), for large container carriers. The resulting database obtained from numerical analysis using OpenFOAM allowed the analysis of correlations between these factors and design variables. This database was then employed to train a deep learning algorithm capable of predicting the effects on fluctuating pressure and erosion index induced by the change of Hi-PSD[®] geometry. Consequently, this trained deep learning algorithm can be utilized to predict fluctuating pressure and erosion index based on Hi-PSD[®] design parameters.

Through this research, a comprehensive design process of Hi-PSD[®] for large commercial vessels is established for predicting cavitation performance, encompassing fluctuating pressure and erosion risk index

Keywords

ESD, Marin Propeller, Cavitation, Hull pressure fluctuation, OpenFOAM

1 INTRODUCTION

In order to comply with the EEDI regulations, which were enacted by the IMO in 2013, newly built ships after 2025 must reduce carbon emissions by at least 30%. (IMO 2013) In order to achieve this, research has been conducted to improve the fuel efficiency of ships in various ways, including propeller design optimization and the development of various devices to improve propeller efficiency. In this study, Hi-PSD[®] (Pre-Swirl Duct), which is a device with fins attached to a half duct that is most commonly applied to the front of a propeller, was used. The geometry of a typical Hi-PSD[®] is as shown in Figure 1. Generally, the left side is used for low-speed bulk/crude oil

carriers and the right side is used for high-speed container carriers.

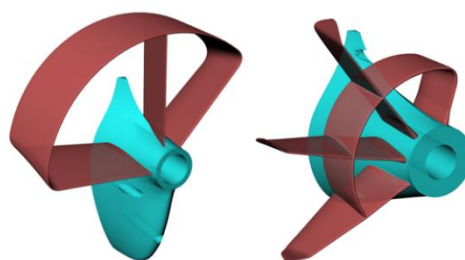


Figure 1. General geometry of Hi-PSD[®]

The propeller erosion index and fluctuating pressure can be significantly changed due to the Hi-PSD[®] attached directly in front of the propeller, affecting the propeller's inflow. It is difficult to predict erosion and fluctuating pressure through existing data. In this study, a deep learning prediction framework was constructed that can predict erosion and fluctuating pressure without additional numerical analysis or experiments, by training a deep learning algorithm on the pattern of erosion index and fluctuating pressure collected in the design stage of the propeller and Hi-PSD[®] based on numerical analysis data.

The design of a propeller that takes into account cavitation, erosion index, and fluctuating pressure requires a significant amount of numerical analysis resources. It is very difficult to improve the performance of the propeller while satisfying all of these conditions. In addition, the acquisition and learning of a large amount of data for deep learning was also one of the difficulties of this study.

In order to conduct this research, the propeller and Hi-PSD[®] were each configured as geometry definition and design variables, and the training data was constructed using sobol sampling. The data for training was obtained through erosion index and hull pressure fluctuation results through wake and cavitation analysis using OpenFOAM, an open-source numerical analysis program. Deep learning was performed through the results of these two numerical analyses, and the results are reviewed in Section 4.

Through this study, it was possible to predict the cavitation risk by estimating rapidly the erosion index and hull pressure fluctuation in the design stage of the propeller and

Hi-PSD[®], and the computational time and resources could be significantly reduced by not going through the numerical analysis process.

2 DESIGN FRAMEWORK

The automated design framework was constructed using commercial optimization software, and its workflow is shown in Figure 2. This workflow can be modified in various ways and will be applied to future research. The components of the design framework are described in detail in this Section.

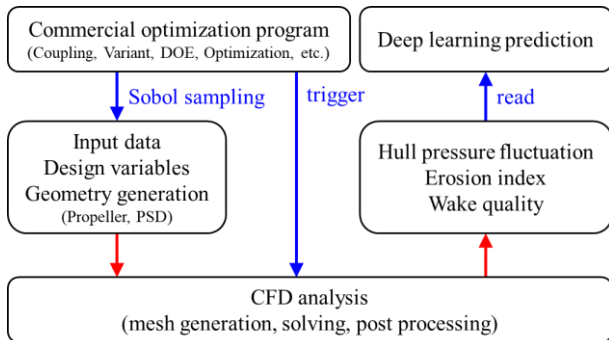


Figure 2. Workflow of automated design framework

2.1 Propeller geometry and design variables

The geometry of a propeller can be basically described in terms of radial distribution functions according to ITTC definition. The propeller geometry is parameterized in its main parameters and its radial distribution functions for pitch, chord, camber, thickness, skew, and rake.

Bezier curves were used to express the distribution function.(Foeth 2013) In reference to Foeth's method, b-spline curves are applied for describing two dimensional distributions of the propeller geometry in this study.(Park 2015)

To make random pitch distributions $p(r)$, 'normalized' curve for pitch distribution is used. It is depicted as 3rd order b-spline curve with 5 control points (P1 ~ P5). P1 and P5 are the end points of the curve and P2 ~P4 are control points for b-spline curve. The other parameters for propeller geometry are represented to similar method using b-splined curve. In this study, the pitch, EAR(Expanded Area Ratio), chord, and skew, which were selected as design variables that define the propeller geometry were used. These variables were reflected in the sobol sampling along with the Hi-PSD design variables described later.

2.2 Hi-PSD geometry and design variables

The most common and effective flow control type fuel saving devices applied to large commercial ships are devices in the form of ducts and fins that can directly control the inflow to the propeller to maximize propulsion efficiency. Ducts and fins can be used independently or in combination to select the most effective devices for each ship. In this study, the Hi-PSD[®], a combination of half duct and fins, which is most commonly used and considered to be the most effective for large commercial ships, was adopted as a fuel-saving device.

Hi-PSD[®] can be combined with a duct and a few fins. The duct makes equalized inflow to the propeller or generates lift forces by itself. In the case of a single skeg type ship, the symmetric inflow of propeller is very inefficient for propeller operation, and fins maximize propulsion efficiency by changing the direction of flow in front of the propeller. In this study, a combination of 1 duct and 3 fins, the most common and simple configuration, was adopted, and the Hi-PSD[®] geometry was made adjustable as a design variable. Hi-PSD[®] is composed of a large number of design variables. However, in this study, the basic design variables were fixed based on experience, and only the key design variables that could affect the propulsion performance of the propeller or meet the purpose of this study were selected as variables.

Based on the NACA section, the following variables were selected for the duct: relative size of the duct based on the propeller, angle of attack of the duct section, and length of the duct in the longitudinal direction of the ship. The fins are based on the NACA section, with the main variables being the cylindrical position of the fins on the port, center, and starboard sides, and the angle of attack of each fin. In addition to these, there are many variables that determine the geometry of Hi-PSD[®]. However, in this study, only the main variables that can be utilized in deep learning were selected for machine learning.

2.3 Sobol sampling

In order to save computing resources for numerical analysis, the most efficient strategy is needed during global searching procedure. In this sense, sobol sampling is applied for this study. Sobol sampling is a Monte Carlo method for estimating the statistical properties of high-dimensional functions. Sobol sampling generates a point sequence that fills the design space more uniformly than a random sequence. This helps to reduce the computational resources and estimate the characteristics of the design space more accurately. Sobol sampling is performed in the following steps. It divides the design space into a n-dimensional hypercube and subdivides each hypercube into n-subcube. And then it generates a sequence consisting of one point in each subcube. It evaluates the high-dimensional function using the generated sequence.

By a global search using sobol sampling, it is possible to understand the characteristics of design space and relationships between evaluation values and design variables. Global search intrinsically leads designers to the further intuition for large design space with many design variables. The results by global search can be also useful for finding good starting points for an additional design optimization. Sobol sampling does not require derivatives and is easy to understand. So that, it is used in various fields such as optimization, statistics, signal processing and machine learning etc. In general, Sobol sampling is the best choice for sampling high-dimensional functions. It is more accurate and efficient than other sampling methods, such as random sampling and Latin hypercube sampling. However, sobol sampling cannot be applied to low-

dimensional problems, and it can be computationally expensive for very high-dimensional problems.

The database for deep learning in this study was constructed using sobol sampling, taking into account these considerations.

3 DEEP LEARNING PREDICTION

3.1 OpenFOAM

The analysis of cavitation in marine propeller is inherently complex due to the highly unsteady flow conditions resulting from the presence of a hull fitted with Hi-PSD, which introduces disturbances into the flow. To accurately predict cavitation performance, CFD with RANS turbulence modeling has become the preferred tool for conducting this analysis. However, the demand for accurate simulation has increased. When applying Large Eddy Simulation (LES) for high-resolution analysis, it becomes imperative to employ a substantial grid resolution, leading to significant computational costs. In contrast, Reynolds-Averaged Navier-Stokes (RANS) analysis relies on time-averaged modeling, which comes with inherent limitations in capturing rapidly changing cavitation patterns. In this study, we implemented a hybrid turbulence modeling approach to compromise advantage LES and RANS. (Kang, 2022) Within the framework of the hybrid model, RANS and LES models are integrated and weighted according to predefined regions described Eq. (1).

$$\tau_{ij}^{hybrid} = w_1 \tau_{ij}^{LES} + w_2 \tau_{ij}^{RANS} \quad (1)$$

$w_1 + w_2 = 1, w = \text{weight factor}$

Consequently, LES is employed to provide a high-fidelity analysis of the propeller's cavitation region, while RANS ensures computational stability in the remaining regions.

3.1 CFD analysis

During the design phase, accurately predicting cavitation performance, including factors like erosion risk and hull pressure fluctuations resulting from cavitation, is of paramount importance. As previously mentioned, cavitation analysis for marine propellers is conventionally conducted using CFD, a method that incurs significant computational expenses. In this study, we present an alternative approach. To implement this approach, deep learning algorithm is employed to predict erosion indices and pressure fluctuation values. This prediction was applied by employing a dataset generated from CFD simulations. The dataset creation process was executed using the open-source software OpenFOAM 7.0. This analysis primarily was focused on large commercial vessel, with specific emphasis placed on variations in propeller design and the Hi-PSD[®] according to design parameters.

Pressure variations occur as cavitation forms, develops and dissipates. The extent of unstable pressure fluctuations can potentially lead to structural damage, depending on the magnitude of the pressure peaks.

Figure 3 is a graph comparing the pressure fluctuation results calculated by OpenFOAM used in this study with

the pressure fluctuation results of the model test. As can be seen in the graph, the error is within about 0.5 kPa. This result demonstrates applicability of estimation pressure using OpenFOAM.

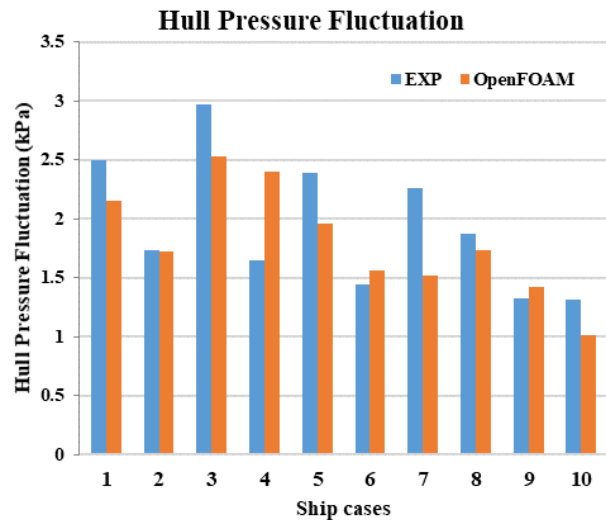


Figure 3. Pressure fluctuation comparison of EXP&CFD

Previous research has involved calculating an erosion index through CFD and subsequently comparing it with experimental data to establish a correlation. (Hasuike 2009) In this study, one of the erosion indices previously employed in these investigations was chosen and used as a basis for machine learning.

$$Erosion\ index = a \cdot \max[p - p_v], 0] \quad (2)$$

p : pressure on the propeller
 p_v : vapor pressure

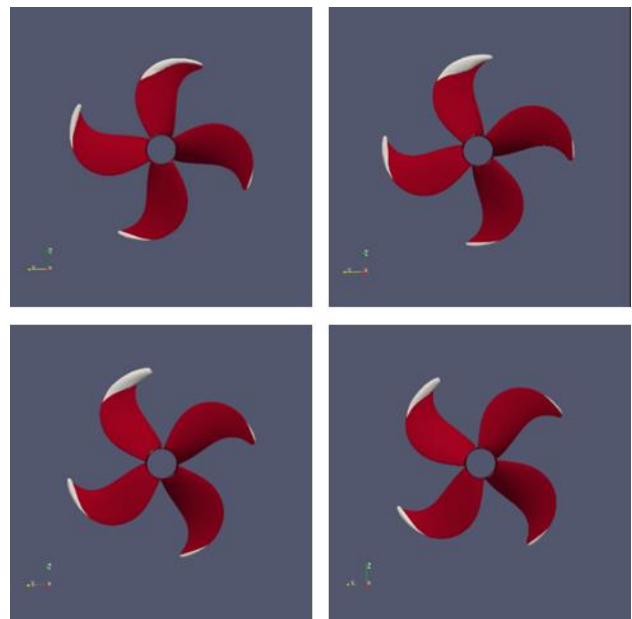


Figure 4. Cavitation pattern on propeller blade

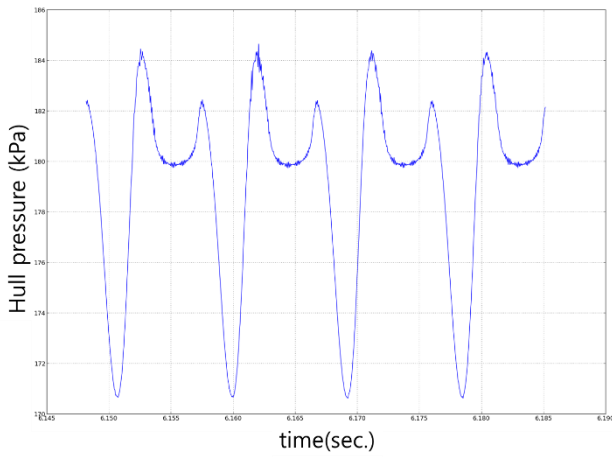


Figure 5. Time history of hull pressure

The results, as shown in the Figure 4, were obtained using OpenFOAM. The figure is an iso-surface of VOF at 0.05, and it illustrates the dynamic process of cavitation formation, development and dissipation in response to the direction of rotation. Figure 5 shows the temporal evolution of pressure at a position directly above the propeller. Subsequently, the principal components of the erosion index and variable pressure, with a specific focus on their variations in response to changes in propeller and Hi-PSD, were employed in a deep learning framework for prediction modeling.

3.3 Deep learning algorithm

In recent studies, there has been a notable trend in research efforts for the capabilities of deep learning algorithms. This trend has extended to the realm of marine propeller applications, with numerous studies exploring the potential of artificial neural networks for learning and predicting ship noise using deep learning methodologies. (M. Thomas 2020)

The prior study focused primarily on the shape design of propellers. Nevertheless, it is well-established that not only the propellers themselves but also the inflow conditions significantly influence propeller cavitation. In this current research, the objective is to comprehend the impact of both propeller and appendage design on the inflow conditions. Specifically, this study aims to predict the outcomes by deep learning algorithms, utilizing Hi-PSD[®] and propeller design variables. The deep learning algorithm was employed with three models, each designed for the purpose of estimating the fluctuation pressure and erosion index, respectively. Model 1 was designed with a network architecture comprising nine layers. Model 2 featured eleven layers, with the number of nodes per layer reduced from 100 to 50 compared to Model 1. Model 3 was configured with seven layers, each containing 200 nodes. In all three models, the rectified linear unit (ReLU) function was employed as the activation function. Additionally, to mitigate overfitting, L2 regularization and dropout were applied to each layer.

Table 1. Deep learning Model 1

Layer (type)	Output Shape	Parameter
dense	(None, 50)	1,150
dense	(None, 100)	5,100
dropout	(None, 100)	0
dense	(None, 100)	10,100
dropout	(None, 100)	0
dense	(None, 100)	10,100
dropout	(None, 100)	0
dense	(None, 100)	10,100
dropout	(None, 100)	0
dense	(None, 1)	101
Total parameters:		36,651
Trainable parameters:		36,651
Non-trainable parameters:		0

Table 2. Deep learning Model 2

Layer (type)	Output Shape	Parameter
dense	(None, 50)	1,150
dense	(None, 50)	2,550
dropout	(None, 50)	0
dense	(None, 50)	2,550
dropout	(None, 50)	0
dense	(None, 50)	2,550
dropout	(None, 50)	0
dense	(None, 50)	2,550
dropout	(None, 50)	0
dense	(None, 50)	2,550
dropout	(None, 50)	0
dense	(None, 1)	51
Total parameters:		13,951
Trainable parameters:		13,951
Non-trainable parameters:		0

Table 3. Deep learning Model 3

Layer (type)	Output Shape	Parameter
dense	(None, 50)	1,150
dense	(None, 200)	10,200
dropout	(None, 200)	0
dense	(None, 200)	40,200
dropout	(None, 200)	0
dense	(None, 200)	40,200
dropout	(None, 200)	0
dense	(None, 1)	201
Total parameters:		91,951
Trainable parameters:		91,951
Non-trainable parameters:		0

3.4 Result

The deep learning process was applied via three deep learning models, denoted as Models 1, 2 and 3, for the prediction of 1st BPF (Blade passing frequency) of hull pressure fluctuation value. The learning utilized propeller design variables, and it ran for 500 epochs. The results indicate that the training loss and validation loss start to converse, suggesting a potential overfitting issue in the learning process. This difference between the training and validation loss values is illustrated in the Figure 6. The cost function's loss is determined as the root mean square between the predicted values and the corresponding training or validation data.

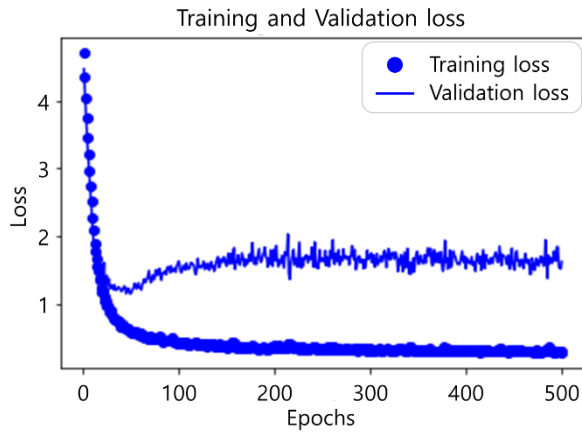


Figure 6. Training and validation loss of Model 1

Hull pressure fluctuation

Table 4 shows the results obtained when using only propeller design variables and when combining propeller and Hi-PSD[®] design variables. When exclusively using propeller design variables, it is evident that the average error in the training dataset is less than 5%.

However, the standard deviation exceeds 10%, indicating significant variability in the results. The validation results for all models also exhibit standard deviations exceeding 20%, which is indicative of overfitting.

To address the concern of overfitting, the addition of Hi-PSD[®] design variables was incorporated for the prediction of variable pressure. This modification led to relatively smaller values in both the training and validation datasets compared to the previous results. Model 3, in particular, demonstrated improved results in terms of standard deviation for both training and validation errors when using both propeller and Hi-PSD[®] design variables. Nevertheless, it is worth noting that the high standard deviation in the validation error may persist due to the insufficiency of the data compared to when both propeller and Hi-PSD design variables are employed.

Erosion Index

The erosion index was applied to deep learning process. The previously established Models 1, 2, and 3 were applied in the prediction of the fluctuating pressure. The study compared the results of applying only the propeller design variables with those of learning both the propeller and Hi-PSD design variables together.

Table 4. Averaged error and standard deviation of each deep learning model for hull pressure fluctuation

Train Parameter		Prop. geo.			Prop. geo & Hi-PSD geo.		
Deep learning model		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Train	avg.	2.2%	4.5%	-1.3%	2.4%	0.5%	-0.6%
	std.	13.3%	13.6%	12.6%	5.7%	7.1%	4.4%
Valid ation	avg.	-0.4%	-2.3%	8.5%	5.2%	10.3%	10.6%
	std.	31.8%	19.4%	30.4%	32.2%	56.3%	24.0%

In the case of the erosion index, the data distribution is notably diverse, unlike the results observed for fluctuating pressure. It was anticipated that this wide data distribution might impact the accuracy of the learning process. Tables 4 and 5 and Figures 7, 8, 9, and 10 show the results learned from each deep learning model.

As depicted in the table, when utilizing only the propeller geometry for prediction, the standard deviation of the training data errors ranged from 50% to 90%, which is notably higher than what was observed for fluctuating pressure. As previously mentioned, it is evident that the wide distribution of the erosion index data significantly affects the learning process.

Notably, Model 3 demonstrated the most favorable results when both propeller and Hi-PSD[®] geometries were employed together. The standard deviation of the training data errors and validation data errors exhibited superior performance among the various models tested.

Table 5. Averaged error and standard deviation of each deep learning model for erosion index

Train Parameter		Prop. geo.			Prop. Geo & Hi-PSD geo.		
Deep learning model		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Train	avg.	21.8%	24.6%	21.1%	8.0%	23.2%	11.8%
	std.	92.5%	56.4%	89.6%	47.1%	62.2%	46.7%
Valid ation	avg.	165.2%	124.4%	101.7%	110.2%	75.4%	64.5%
	std.	165.2%	208.7%	300.2%	315.7%	174.5%	133.1%

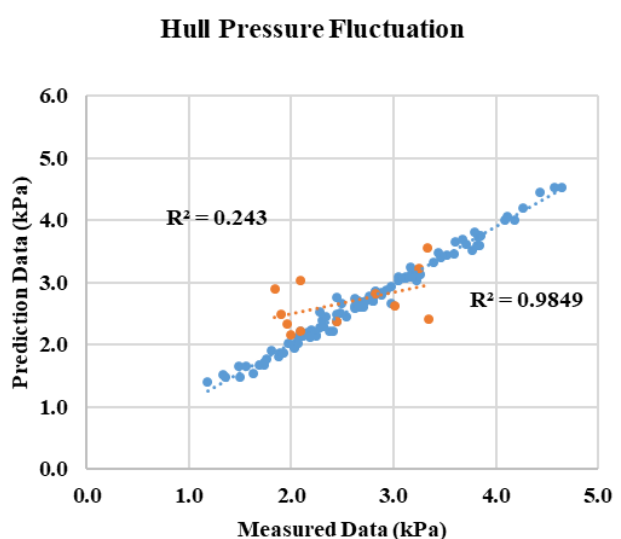
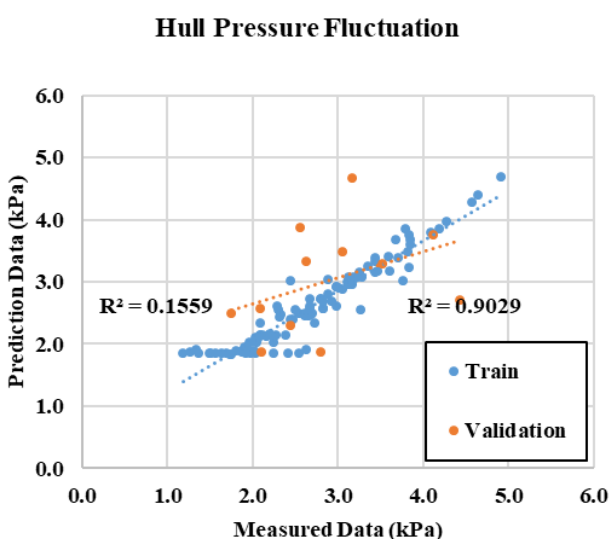
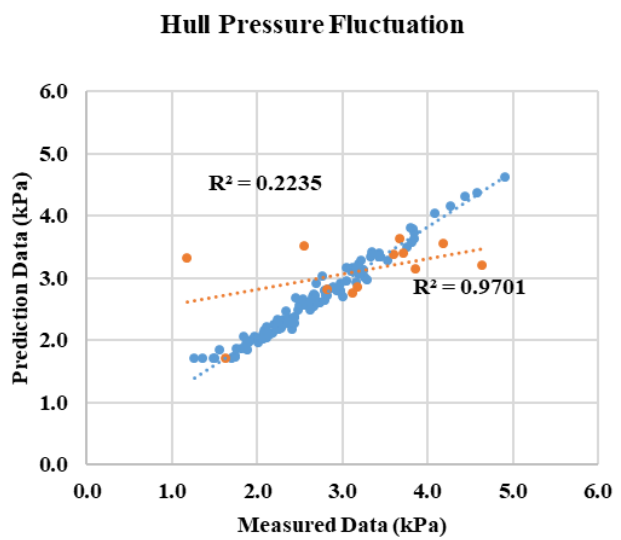
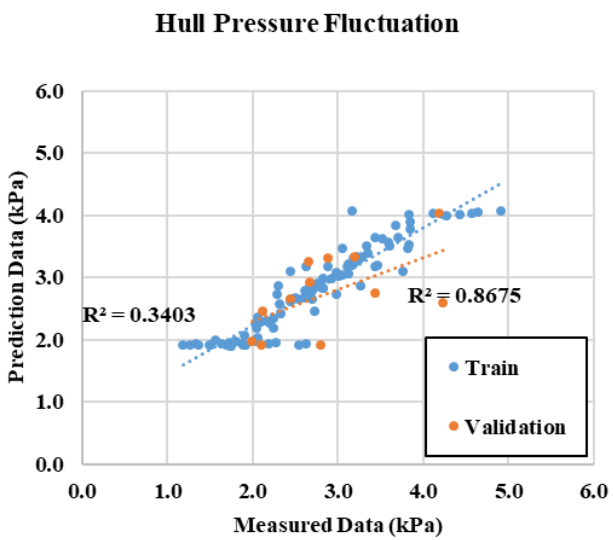
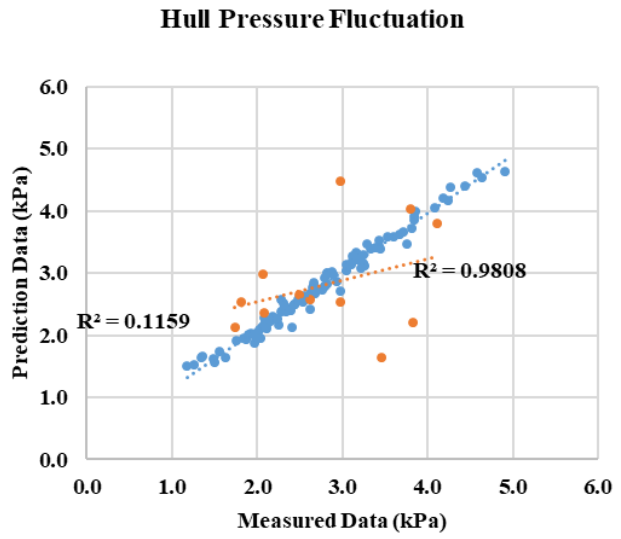
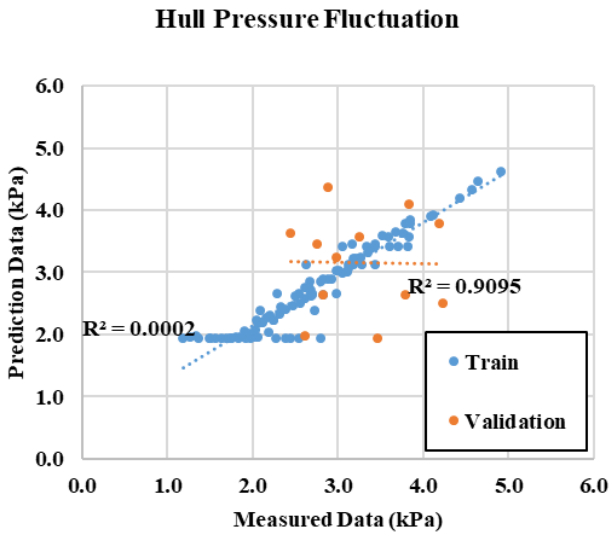


Figure 7 Hull Pressure Fluctuation
 - Model 1, 2, and 3 only propeller design variables

Figure 8 Hull Pressure Fluctuation
 - Model 1, 2, and 3 propeller and Hi-PSD design variables

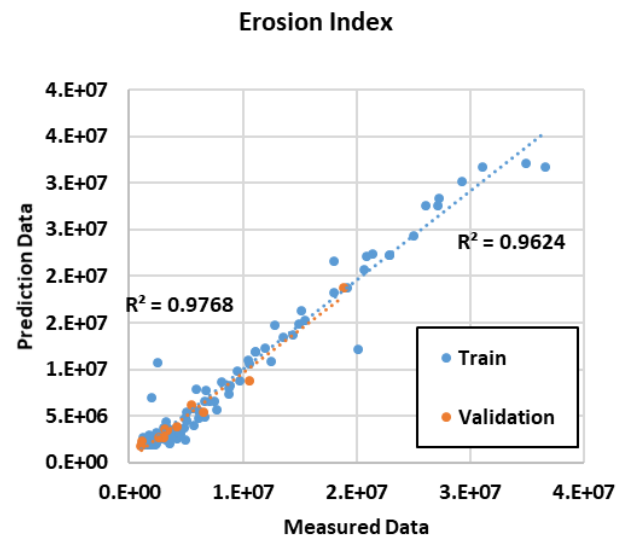
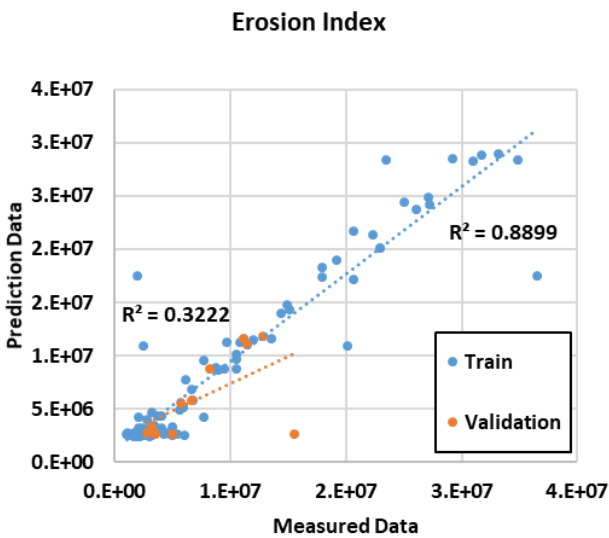
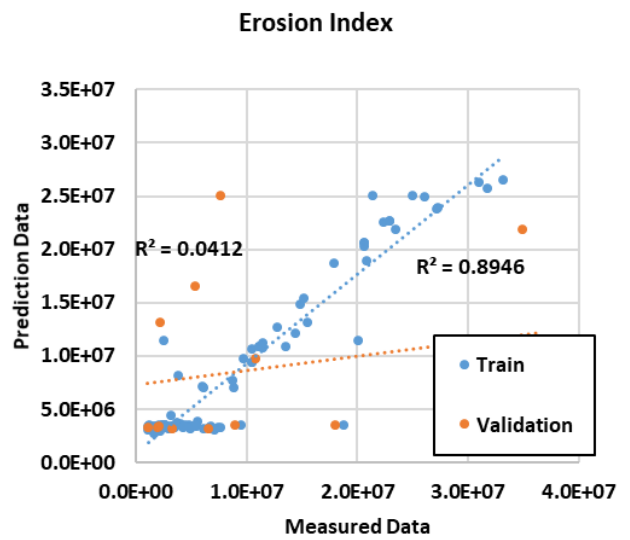
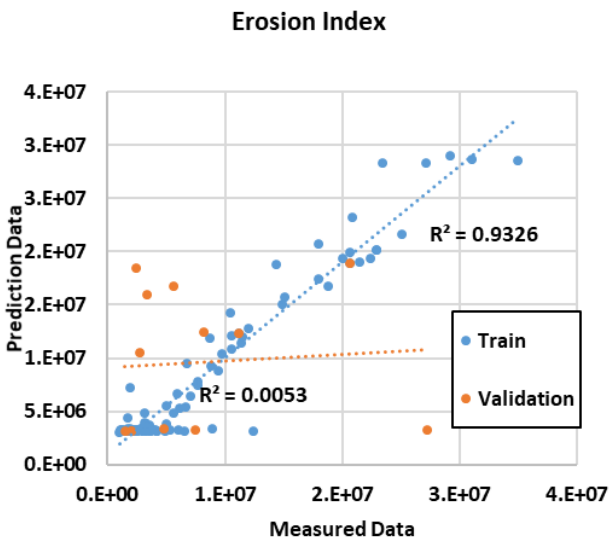
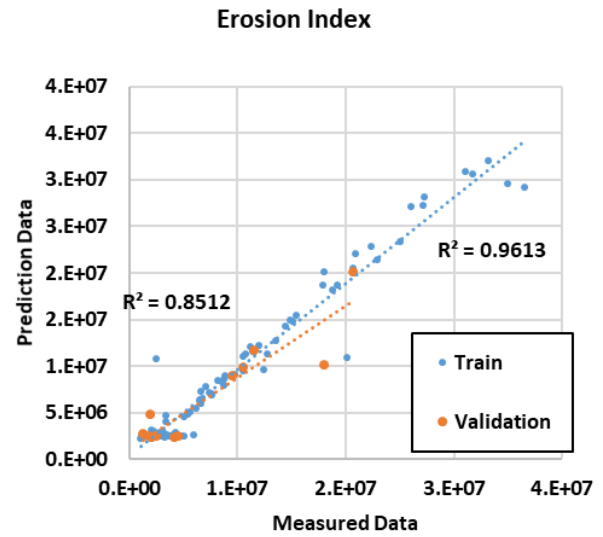
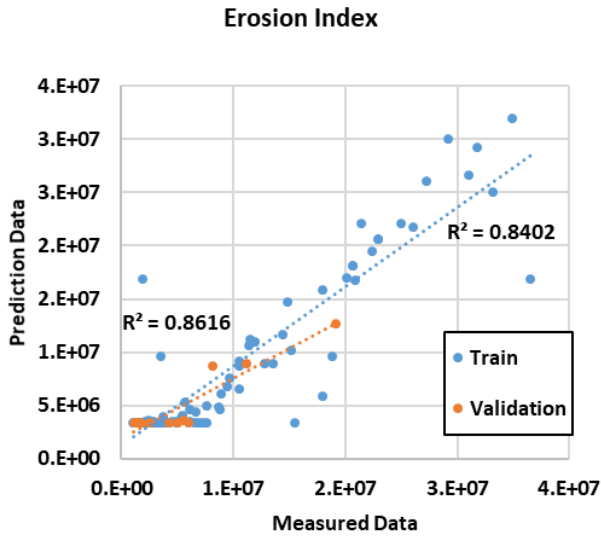


Figure 9 Erosion Index

- Model 1,2 and 3 only propeller design variables

Figure 10 Erosion Index

- Model 1,2 and 3 propeller and Hi-PSD design variables

4 CONCLUSION

This study presents a latest procedure for predicting fluctuating pressure and erosion risk caused by cavitation, utilizing deep learning with numerical analysis. Deep learning was trained using a dataset of numerical analysis results obtained using sobol sampling and OpenFOAM with a fully parameterized design method. Specifically, by analyzing Computational Fluid Dynamics (CFD) results of ships equipped with the fuel-saving device Hi-PSD[®], it is proposed that combining deep learning algorithms with input flow information (Hi-PSD[®] design variables) and propeller design variables can improve the accuracy of the learning results. This demonstrates the close relationship between Energy Saving Devices (ESDs), such as Hi-PSD, and the performance estimation of propulsion systems in most modern ships where fuel-saving devices are applied. This outcome underscores the efficacy of the propeller with Hi-PSD[®] design procedure in integrating propeller and ESDs. Future research will involve performing simulations with more comprehensive datasets and various types of ships. Subsequent studies will explore ways to maximize fuel efficiency in ships using optimization algorithms through deep learning.

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