WHITE PAPER

Data Science for hydromechanics simulation in the maritime industry

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Introduction

In the heart of maritime innovation, Damen Shipyards stands at the forefront by seamlessly blending traditional shipbuilding craftsmanship with modern technology. As the industry's demand for more efficient and intelligent vessels increases, data science has emerged as a vital component in engineering calculations. Terms like "machine learning" (ML) and "artificial intelligence" (AI) have become industry buzzwords, but they signify real advancements in engineering calculations. By enabling complex analyses, pattern recognition, and predictive modelling, data science, and AI provide engineers with powerful tools to solve challenges faster and with great precision. For the shipbuilding industry, these technologies hold the potential to accelerate and enhance computational tasks that were once labour-intensive, paving the way for more informed decision-making and innovative design solutions (Figure 1).

Figure 1: Digitalization of the shipbuilding industry using AI targeting to improve vessel design and operational performance. The figure is generated using an AI image generator.

Within Damen, computational numerical simulations play a pivotal role in hydromechanics, structural, noise, and vibration analysis. These high-fidelity numerical models are essential for providing detailed and accurate predictions that underpin the optimization and performance assessment of vessel designs. During the early design stage, advanced mathematical techniques and high-performance computing resources are employed to model complex marine interactions accurately, while skilled engineers and analysts ensure that simulations yield meaningful and actionable insights. Physics-based models rely on established equations to ensure accuracy, but they come with high computational demands that often prolong the design process, limiting the frequency of design iterations and hindering the pace of optimization efforts. Additionally, these models require detailed information for the computations, which is not always readily available during the early design stages. Moreover, the necessary pre-processing time for computational simulations, beginning with the design and model preparation is rising significantly when handling complex geometries like hulls. This further results in a substantial increase in human hours during the early design stage of a vessel.

At the same time, Damen faces increasing pressure to deliver fast and accurate design solutions for our customers' needs. To overcome the simulation constraints of conventional methods and reduce the lead time of the Computation Fluid Dynamics (CFD) predictions, Damen's RD&I department has embraced digitalization by integrating AI with traditional physics-based calculations. In this way, hydromechanics simulations are significantly accelerated. Over the past year, Damen's RD&I Data Science activities have led to an ML pipeline to optimize vessel resistance in calm water, a key factor for improving energy efficiency. Advanced AI techniques have been designed and tested, incorporating various ML models to balance accuracy and computational speed. The goal was to develop an ML approach trained on offshore patrol vessel (OPV) designs to predict hydromechanics resistance (Figure 2).

In this white paper, the modelling approach for the fast hydromechanics resistance prediction using ML is described and the recently proposed methodology of developing a Fast Physics AI-based solver using 3D simulations within Damen is presented. Moreover, the impact of applying data science in the maritime industry is clarified.

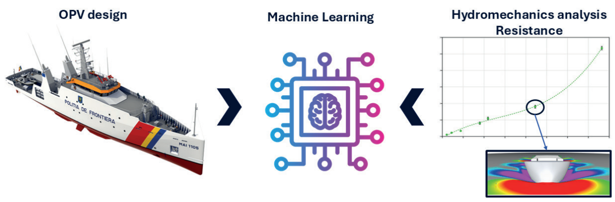

Figure 2: Machine learning pipeline receiving the geometry of OPV vessels and predicting the hydromechanics resistance.

Background

For many years, Damen's RD&I department has underscored the importance of systematically storing hull information, including geometries and data generated from hydromechanics simulations, model tests, and sea trials in a well-structured, high-quality database. This approach ensures that valuable insights can be effectively reused for future projects, providing long-term benefits to both internal teams and external clients. Along with that, in 2021, Damen implemented a novel method for hull design that made it possible to anticipate decisions having a critical impact on hull resistance at the very early stages of ship design. This approach markedly improved the quality of hull designs, making the process more streamlined and efficient.

Over the past decades, physics-based, analytical methods have been developed and commonly utilized in the maritime industry, to speed up the vessel design process, by predicting the hydrodynamic resistance of a hull using its main dimensions and coefficients. One of the most important aspects of predictions based on analytics regressions is that they are fast enough to apply and allow the designer to make an informed choice of hull coefficients before starting the long process of designing a geometry. However, these methods have significant limitations since they only apply to very conventional hull shapes and parameter sets, often failing to capture intricate details and local variations in hull form that may affect performance. Moreover, these regression methods mostly consider the main dimensions of the vessel and cannot predict the nuanced impacts of smaller changes in the hull shape. When input data deviates from the typical application range, these methods tend to produce unrealistic or unreliable results.

Machine learning modelling

To mitigate the issue related to the rough estimations of traditional mathematical formulas, an ML-based pipeline has recently been proposed. The ML model took advantage of the centralized database containing existing hull geometries and associated performance data extracted from computational hydromechanics simulations conducted during the design phase. In particular, the ML model is employed using hull geometry data to predict the total resistance, replacing the analytical model that is based on traditional mathematical formulas and does not incorporate the high-fidelity simulation data that is available within Damen.

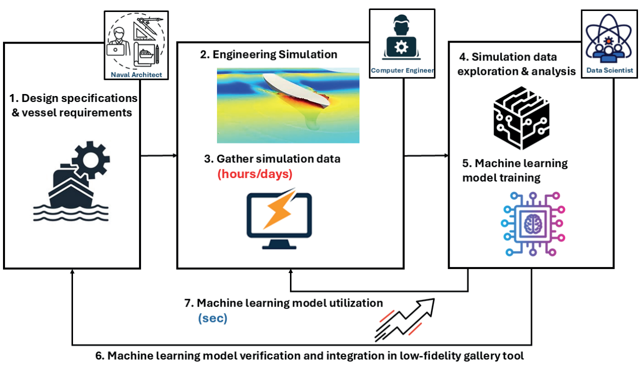

Figure 3: Pipeline of collaboration between the naval architect, the computer engineer, and the data scientist for the data preparation, the machine learning model training, and utilization.

To accomplish this process, collaboration among naval architects, computer engineers, and data scientists was essential (Figure 3). Naval architects at Damen provided detailed vessel designs and performance requirements to the computer engineers. The computer engineers then prepared the engineering simulations and gathered the necessary data to train the ML models. In general, depending on the volume and complexity of the required data, this stage can take days or even months to complete. Once the database was established, data scientists analysed and explored its features, identifying patterns and relationships critical for the modelling process. Then, the AI pipeline was designed, and the performance was tested and evaluated using various ML models and techniques to identify the most effective approach. Sophisticated data processing and model training methods were applied to develop an optimal ML model. This model was then subsequently reviewed and verified by the naval architects to ensure it aligns with the vessel's design goals and performance criteria. After verification, the ML model is now integrated into Damen's toolbox to provide business value for the organization. These ML models enable predictions to be made quickly, often in real-time, dramatically reducing computation times while maintaining accuracy. This streamlined process facilitates efficient vessel design and enhances overall performance optimization.

The outcome of the AI pipeline was that the predicted results from the trained ML model, utilizing CFD data from internally generated systematic series of offshore patrol vessels (OPVs), have already outperformed traditional predictions based on the mathematical analytical formulas. The ML model can accurately predict the hull's resistance, targeting to assist the designer in finding the optimal design that will lead to a lower hull resistance and will empower designers to develop fuel-efficient, high-performance vessels. Moreover, the ability of the ML model to automate and accelerate the design process of new vessels and potentially open new horizons to integrate it with the optimization process and generative AI to discover new geometries.

By integrating the developed ML model into our design process, Damen can deliver near-instant customer feedback by transforming the process of resistance prediction enabling a more dynamic and iterative early design stage. This approach not only accelerates the workflow but also enhances optimization by allowing engineers to explore a wider range of design parameters, crucial for factors such as fuel efficiency, speed, and environmental impact. Future steps involve integrating the trained ML pipeline into engineering software and enhancing its accessibility for shipbuilding professionals. This integration aims to provide significant value by streamlining workflows and supporting engineers and designers in optimizing vessel performance.

Vision and future developments

The demand for fast physics simulation in the shipbuilding sector is growing rapidly, driven by the need for innovation, efficiency, and cost-effectiveness in the design and manufacturing process. Integrating AI to accelerate these simulations is especially beneficial in addressing the complexities and challenges in ship design and operation. Reducing the computational cost of simulations directly translates to savings in both time and money. The designers by using AI can identify design flaws early in the process, avoiding costly revisions later in the production cycle. As a further step, AI can help optimize the vessels' designs by running multiple simulations quickly, identifying the best configurations for performance, weight, and cost efficiency.

Currently, we have successfully developed an ML model capable of predicting total resistance for hull designs providing a single output value derived from geometry and associated physical parameters. While this is a significant milestone, it represents only the beginning of the potential applications of ML in CFD within our operations. Looking ahead, our ambition is to extend this capability toward predicting full 3D CFD results. This would involve creating what we call a Fast Physics AI-based solver using sophisticated ML algorithms capable of analysing and predicting the complex 3D flow fields, pressure distributions, and other physical phenomena surrounding the hull geometry. Such models would generate detailed volumetric predictions, enabling faster and more precise optimization of hull designs across multiple performance metrics. Achieving this vision, however, requires substantial investment in research, development, and computational infrastructure. It also demands expertise in advanced ML techniques, large-scale data handling, and close integration of domain-specific knowledge in fluid dynamics. While some companies currently provide services in this domain, partnering with them entails challenges such as significant costs and the need to share sensitive intellectual property (IP). The black-box nature of their solutions further limits our ability to interrogate, understand, or refine the models for our specific needs. By developing this capability in-house, we would not only maintain control over our IP but also create a transparent, customizable framework tailored to our design requirements and future innovations.

Moreover, while this paper has thus far focused on CFD, the Fast Physics AI-based solver would be a computational field agnostic, which means the base of the models would be viable for many other simulation tasks, such as seakeeping ability, structural analysis, vibration propagation, and manoeuvring.

In this direction, additional investment in computational power will be required, to improve our current high-performance computing resources aiming to generate more simulation data, as well as prepare the machine learning modes.

Conclusions

The exploration of using AI in predicting hull resistance and optimizing designs confirmed the possibility of utilizing computational results to streamline an AI pipeline to significantly aid in the design process, minimising computational efforts while high accuracy is maintained. By facilitating more rapid and frequent design iterations it enables engineers to explore a broader range of design characteristics and reduce design costs and lead times, enabling Damen to build safer, more efficient vessels while reducing their environmental footprint. Based on the current advancements Data Science has proven to be a transformative step for Damen, in the area of hydromechanics analysis, by integrating it seamlessly into the design process.

Damen RD&I has demonstrated the promising potential of these advancements, showcasing how technologies like machine learning and artificial intelligence can optimize vessel design, enhance reliability, and improve overall efficiency. This approach underscores Damen’s commitment to innovation and positions the company at the forefront of data-driven maritime solutions. By harnessing the synergy between high-fidelity physics simulations and advanced ML techniques, Damen is poised to revolutionize the design process, enabling faster, more efficient, and collaborative engineering endeavours. Through this transformative initiative, Damen reaffirms its commitment to driving technological advancements and shaping the future of maritime engineering. «