Comparative Analysis of AI-Based Optimisation Techniques for a Conceptual Frigate Hullform Design

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Synopsis

This paper presents the results of an investigation conducted to assess the efficacy of Artificial Intelligence (AI) in optimising the hullform of a conceptual frigate. A frigate, with a length of 130 meters and a top speed of 24 knots, served as the subject for the experiment. A baseline hull was initially designed, and spatial constraints were defined for the study. Three different contractors were invited to optimise the bare hull resistance for various speeds and displacements. The optimisation process considered a weighted grading matrix based on the ship's operational profile.

One contractor employed traditional optimisation techniques, including empirical knowledge, regression series, and the modification of ship hydrostatic characteristics. A parametric hullform model was created to produce candidate designs. Final analysis was made using Computational Fluid Dynamics (CFD). Another contractor utilised machine learning with neural networks, with training data sourced from a parametric hullform model and CFD results. The final contractor employed a combination of a parametric hullform model, T-Search optimisation, potential flow, and CFD, with a specific focus on achieving maximum top speed with the lowest resistance.

Results indicated that traditional techniques improved bare hull resistance by an average of 8%. The use of neural networks significantly outperformed traditional methods, demonstrating a remarkable average improvement of 22% in bare hull resistance. However, a critical observation emerged regarding the optimisation focused on top speed only, where machine learning techniques demonstrated a 28% improvement on resistance. This improvement, however, came at the cost of a notable detriment to lower speeds resistance, resulting in an average overall increase in resistance of 14% across the speed range.

The findings of this study present a dilemma for naval architects and customers alike. While prioritising top-speed optimisation may lead to reduced capital expenditures (CAPEX) due to lower costs associated with machinery and auxiliary systems, it could also result in increased through-life costs due to high resistance at lower speeds, which constitute the majority of operational time at sea. This highlights the importance of a balanced approach and careful consideration when implementing AI-based optimisation techniques in naval vessel design. Ensuring a holistic view of performance and costs throughout the vessel's lifecycle is crucial for making informed decisions.

Keywords: Hull Design; Artificial Intelligence; Hullform Resistance; Optimisation

1. Introduction

Naval frigate design continues to evolve, driven by the imperative to enhance operational capabilities while managing costs and environmental impact. The development of the 130m Adaptable Strike Frigate (ASF) design that was launched at EuroNaval 2022 responded to these challenges. Designed as a light frigate with specialised mine hunting capabilities, the ASF 130 represents a promising platform for future naval operations (see Figure 1).

To further optimise the performance of the ASF 130, three contractors were tasked with refining its hullform resistance using distinct methodologies. These methodologies include the traditional design spiral approach, artificial intelligence (AI) and neural networks, and optimisation software. The objective of this optimisation study was to explore new methods of resistance optimisation within the context of a more integrated simulation-driven design approach.

The adoption of a simulation-driven design approach aims to holistically address all key aspects of ship design, from hullform resistance to subsystem integration. By integrating various design aspects early in the

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conceptualisation phase, this approach seeks to increase the maturity of concept designs while reducing costly design margins that ultimately impact the final price of the vessel.

In this essay, we delve into the comparative analysis of the three methods employed to optimise hullform resistance for the ASF 130 frigate. Through this exploration, we aim to highlight the strengths and limitations of each methodology, as well as their implications for future naval frigate design. Additionally, we examine how these optimisation efforts contribute to the overarching goal of achieving more efficient, cost-effective, and operationally capable naval platforms.

Figure 1: Adaptable Strike Frigate - Conceptual Design

2. Background

In the pursuit of advancing naval ships design, the optimisation of hullform resistance stands as a critical design task. This essay presents the exploration of three distinct methodologies employed to optimise hullform resistance: the traditional design spiral approach, artificial intelligence (AI) and neural networks, and the utilisation of optimisation software. This discussion is contextualised within the framework of the ASF 130 design, poised as a future light frigate with enhanced mine hunting contender for the UK Royal Navy and export. The overarching aim is to achieve a more efficient ship design, thereby reducing both capital expenditure (CapEx) and operational expenditure (OpEx).

The imperative for such optimisation stems from various factors. Foremost is the global drive towards achieving net zero emissions, where maritime operations play a pivotal role. An optimised hullform design can significantly contribute to enhancing vessel efficiency, thereby mitigating environmental impact. Furthermore, optimising hullform resistance is instrumental in improving design margins, ensuring operational capability, and achieving design maturity earlier in the conceptualisation phase.

The traditional design spiral methodology, a tried-and-tested approach, involves iterative cycles of design, analysis, and refinement. While reliable, this method may lack the agility and computational power necessary to explore the vast design space comprehensively. In contrast, the integration of AI and neural networks introduces a paradigm shift by enabling the exploration of a much wider design space. AI algorithms can discern complex patterns and correlations within data, facilitating the identification of optimal hullform configurations that might elude conventional methods.

Moreover, the utilisation of optimisation software offers a systematic approach to fine-tuning hullform resistance. These tools leverage mathematical algorithms to iteratively refine design parameters, maximising performance objectives while adhering to specified constraints. By harnessing the computational prowess of optimisation software allied to resistance numerical prediction tools such as CFD (Computational Fluid Dynamics), naval architects can expedite the design process and unearth innovative solutions.

The significance of hullform optimisation is emphasised by its centrality to the ship's concept design. As the key element upon which various naval architecture sub disciplines are dependent such as seakeeping, manoeuvring or the general arrangement, the hullform dictates vessel performance across a range of operational conditions. Thus, optimising hullform resistance is not merely a technical exercise but an imperative in defining the entire naval ship design in terms the operational capability and environmental sustainability.

In conclusion, the journey for optimising hullform resistance for future frontline naval ships embodies a multifaceted challenge, necessitating the integration of diverse methodologies. The transition from traditional design spiral legacy approaches to AI-driven exploration and optimisation software signifies a shift towards leveraging advanced computational techniques to achieve superior design outcomes. By embracing innovation in

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hullform optimisation, naval architects can define the way for more efficient, environmentally sustainable, and operationally capable naval vessels.

3. Methodology

To maximise the potential of the ASF 130 design, three contractors were employed and tasked with optimising the ASF 130 hullform for barehull resistance. Each contractor adopted a different optimisation approach, as identified in Section 1, allowing each method to be quantified in terms of the resistance performance gains. These methodologies include the traditional design spiral approach, AI and neural networks, and optimisation software.

Each contractor was provided with the same optimisation brief for fairness (including design condition, operational profile and spatial constraints) with the common objective of optimising the design for barehull resistance.

3.1 Optimisation Constraints

The ASF 130 design is a monohull displacement hullform of 130m in length and 18m in beam (see Figure 1). For the optimisation, a number of design constraints were imposed. This comprised of limits on length (overall and waterline), beam and depth at given locations to ensure there would be no conflicts in other areas of the design (shaftline, propeller clearance, tank capacity etc.).

Each contractor was provided with a common target displacement and longitudinal centre of buoyancy (LCB) for each assessed condition for the optimisation.

3.2 Operation Profile & Scoring Matrix

The optimisation was performed for a given operation profile, as shown in Figure 2. The operational profile was provided to each contractor to further inform the optimisation process.

Based on the operational profile, a scoring matrix (as shown in Table 3) was also provided to each contractor to allow a score to be assigned to each new optimised hullform design, quantifying the overall resistance improvement across the speed and displacement range and subsequently lead to the identification of the 'optimal' design.

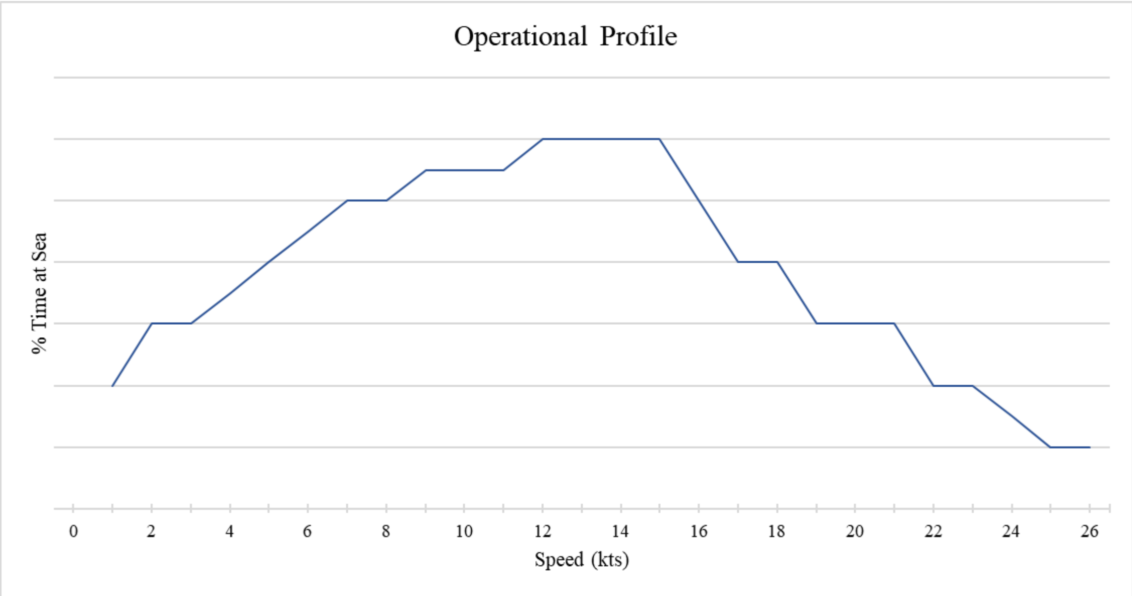

Figure 2: Operational Profile - Typical Frigate

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Table 1: Optimisation Scoring Matrix for a Typical Frigate

Speed (kts)	Displacement Condition			Weighted Total
	Light	Design	Deep	
12	1	5	3	16%
16	2	5	5	21%
20	3	7	7	30%
24	3	7	8	32%
Weighted Total	16%	43%	41%	100%

It should be noted that not all contractors performed the optimisation for the entire operational profile or considered all displacement conditions, therefore only the design condition will be compared for this study to ensure commonality between the results.

3.3 Contractor 1: Traditional Optimisation Method

Traditionally, an existing basis hull form is initially selected based on the target mission objectives, size and performance. The design is 'optimised' using a computer aided design (CAD) software for the specific design brief and ship requirements. Using Rhinoceros Grasshopper, a 3D CAD parametric modelling tool, a hull form is generated based on a series of parameters controlled as inputs within an embedded control panel. The control panel allows for modification of hydrostatic outputs along with the modification of section location and curve controls, resulting in a rapid hull form development and analysis. The Grasshopper script was initially used to re-create the baseline hullform, followed by two development design iterations.

Each design iteration is optimised based on experience, subject matter expert (SME) judgement and inevitably involves an element of good fortune to maintain the hullform design within the boundaries specified by the ship requirements.

3.4 Contractor 2: Artificial Intelligence Optimisation Method

This method adopts AI techniques with intelligently generated CFD analysis to learn trends in the resistance data for various hull shapes. An parametric hullform of the baseline is initially created, with numerous hullform shape parameters each with assigned adjustable ranges (set depending on design constraints and optimisation goals) to create an extensive quantity of unique hullforms.

In this case 500 hullforms were created within the design space and defined constraints, where the resistance of each these design are calculated using CFD. This resistance data is subsequently used to train the neural networks. The optimisation process cycles through the many combinations of hull shapes to achieve the best score against requirements/constraints. The best contenders are then passed back through the CFD and compared with the baseline hull at the defined speeds and displacements.

3.5 Contractor 3: Optimisation Software Method

The third method of optimisation using a 3D Shape Optimisation Software, where a parametric model was created of the baseline hullform design. The software also has integrated capabilities for process automation and shape optimisation. The optimisation software allows you to build robust parametric ship models with smarter shape control. Optimisation and automated design exploration augment the development process leading to better and optimised designs.

Using the optimisation software method, a potential flow solver was used to run an initial design of experiments, followed by a Tangent-Search (T-Search) optimisation. The main purpose of the T-Search method is to identify a descent search direction in the solution space, enabling a rapid improvement in the desired solution direction, whilst maintaining the solution within a feasible design domain.

In this case, a T-Search optimisation was conducted for a maximum of 50 design cases, where 38 feasible designs were created and CFD simulations were subsequently completed, and the optimal design was selected. The method detects a local minimum within the design solution space, where a number of predefined variables are subject to explicit bounds, i.e. a lower and an upper bound, along with any design constraints that apply. If a constraint bound is approached a tangent move in hyperspace is conducted tangential to the constraint either to keep the search in the feasible domain or to bring it back to the feasible domain.

In addition, as a result of the optimisation the software generates graphs showing the relationship of various design parameters and variables, allowing sensitivity analysis of design parameters to be understood.

4. Optimisation Results

The baseline hullform was ‘optimised’ using the previously described techniques; Traditional Methods (Contractor 1), AI and Neural Networks (Contractor 2), and Optimisation Software (Contractor 3). Refer to Table 2 and Figure 3 for the resulting optimised hullform designs.

Using the traditional optimisation method, the optimised hullform results in some minor changes from the baseline design including a reduction in volume made in the bow and reducing the half angle of entrance (HAE), the LCB was moved further aft by 1%, and a reduction in the bilge radius aft of midships.

Using AI and neural networks, there were modifications made to the beam (an increase in 10%) at midships, transom knuckle height was increased, reduced block coefficient at the transom section, finer bow entry, amongst other changes.

Contractor 3, using the shape optimisation software, only optimised the baseline design for top speed and not the entire speed range. Therefore the optimised hullform design is notably different to the baseline and other optimised designs, this is most prominent at the bow.

The optimised design by each contractor differ from the baseline most notably at the bow, this was due to their being a specific optimisation constraint in terms of a given minimum beam in order to accommodate a particular combat system compartment located in the forward part of the ship.

Table 2: Optimised Hullform Hydrostatic Parameters

Parameter	**Baseline**	**Traditional Method (Contractor 1)**	**AI & Neural Networks (Contractor 2)**	**Optimisation Software (Contractor 3)**
Block Coefficient	0.492	0.494	0.478	0.492
Midships Coefficient	0.784	0.809	0.790	0.837
Prismatic Coefficient	0.628	0.610	0.605	0.588
Waterplane Coefficient	0.820	0.808	0.720	0.784

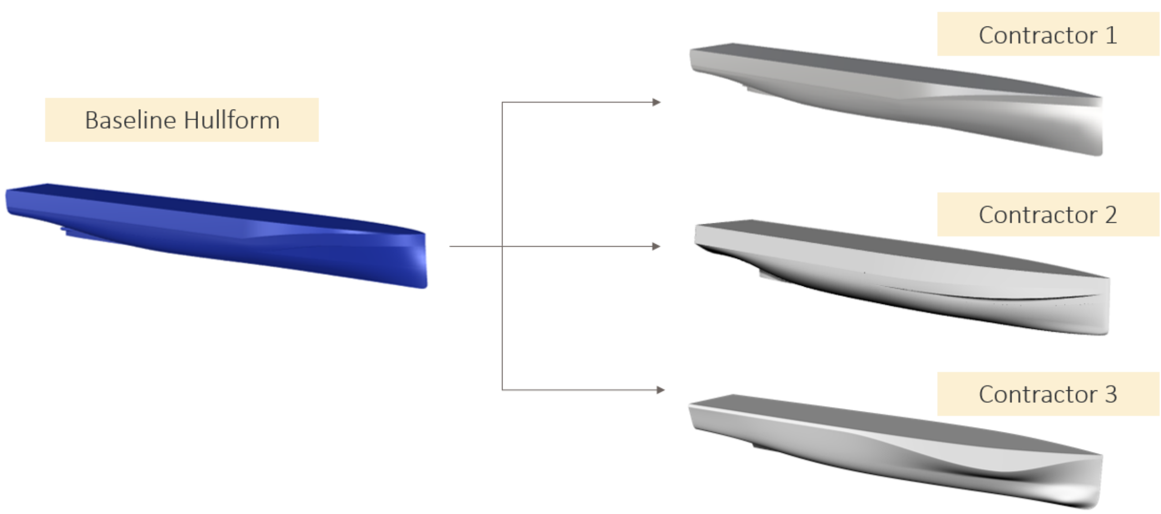

Figure 3: Optimised Hullforms

As previously discussed, for each optimisation method only one ship loading condition was assessed by all contractors, therefore the results are presented solely for the design condition.

AI and neural networks method (Contractor 2) proved to be the most effective in terms of the achieved average resistance reduction over the entire speed range. However, the method adopted by Contractor 3 showed the greatest resistance reduction at top speed, with a 28% reduction against the baseline design in the Design

Condition. Refer to Table 3 and Figure 4 for the comprehensive results for the design condition for each Contractor.

Table 3: Design Condition - Optimisation Results

	Contractor 1	**Contractor 2**	**Contractor 3***
Ship Speed (kts)	**% from Baseline**	**% from Baseline**	**% from Baseline**
12	-10.5%	-19.3%	+98.0%
16	-10.6%	-26.5%	+13.0%
20	-6.3%	-22.2%	-26.0%
24	-4.8%	-18.2%	-28.0%
Average:	***-8.0%***	***-21.6%***	***+14.3%***

*Hullform optimised for top speed only.

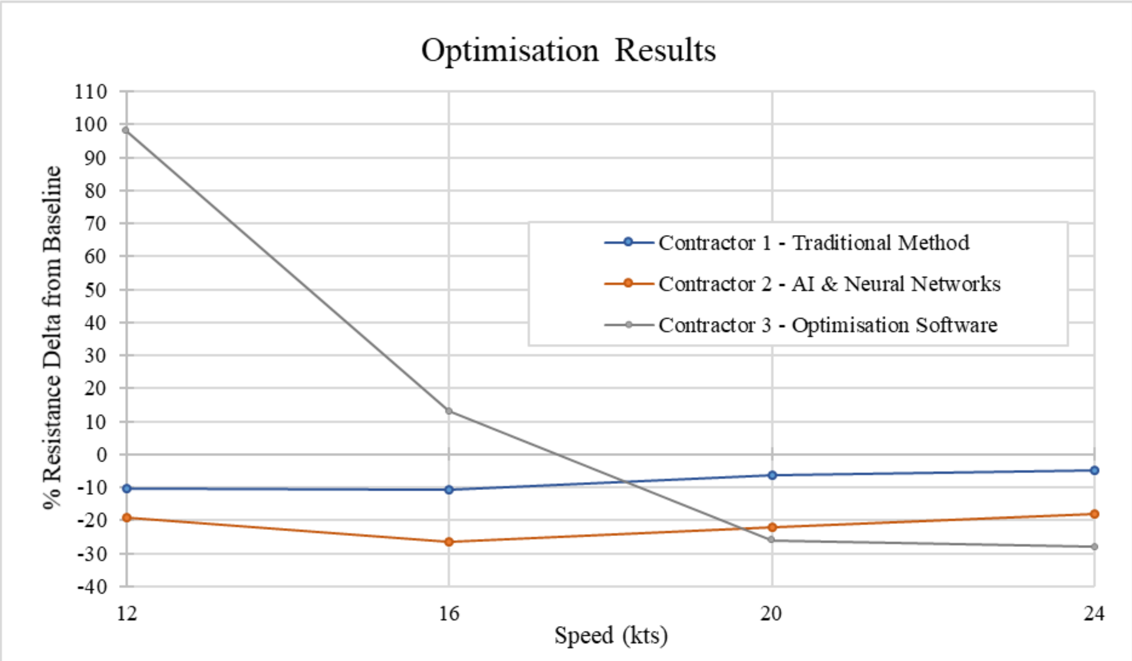

Figure 4: Design Condition - Optimisation Results

Using the scoring matrix presented in Table 1, each optimised hullform was subsequently 'scored', where the lowest scoring hullform represents the most efficient resistance hullform across the speed range. For the design condition only (the common condition), the score for each hullform is presented in Table 4.

Table 4: Scoring for Design Condition

	Method	**Score**
Contractor 1	Traditional	93.9
Contractor 2	Artificial Intelligence	78.0
Contractor 3	Optimisation Software	102.3

The resulting impact on wake, appendage design, appendage alignment, and propulsive coefficients on each of the optimised ASF 130 hullform designs were not assessed for this study. During the concept phase, the hullform design informs each of these design characteristics, therefore it would not be fair to compare these parameters to the baseline design, especially as the ASF 130 design is in early development.

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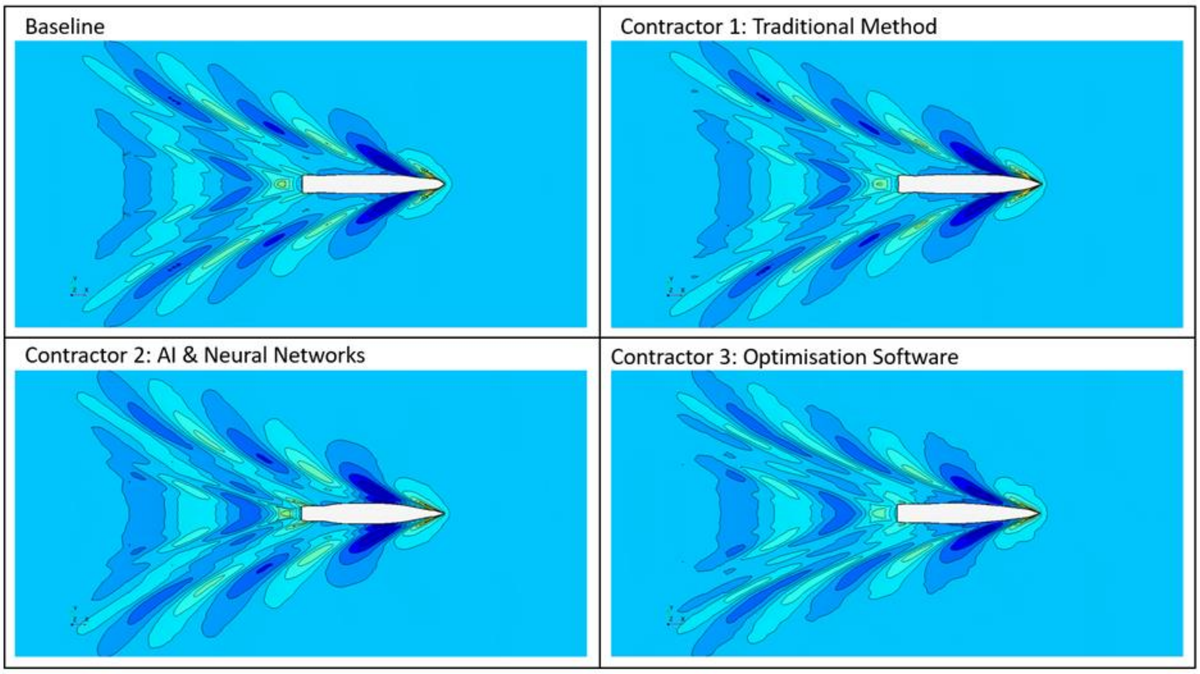

Figure 5: Design Condition at 24kts - Free Surface (Plan View)

5. Validation

The results presented in Table *3* were based on the optimisation performed by each contractor. The resulting optimised hullform designs were provided to BAE Systems where the barehull resistance results were subsequently validated by completing a CFD analysis (using STAR CCM+ version 2020.2 (15.04.008)). The validation was conducted using the same discretisation and physical models for each optimised design, with mesh refinements for areas with more complex flow characteristics such the stern and bow positions (refer to Figure 6). The free surface was modelled using the Volume of Fraction (VOF) and Moving Reference of Frame (MRF) to account for the running sinkage and trim of the vessel, wall functions were also used. The selected turbulence model used for the simulations was the K-Omega Shear Stress Transport (SST). Each CFD validation used approximately 1.6 million cells and each simulation used an average of 128 cores to complete the analysis.

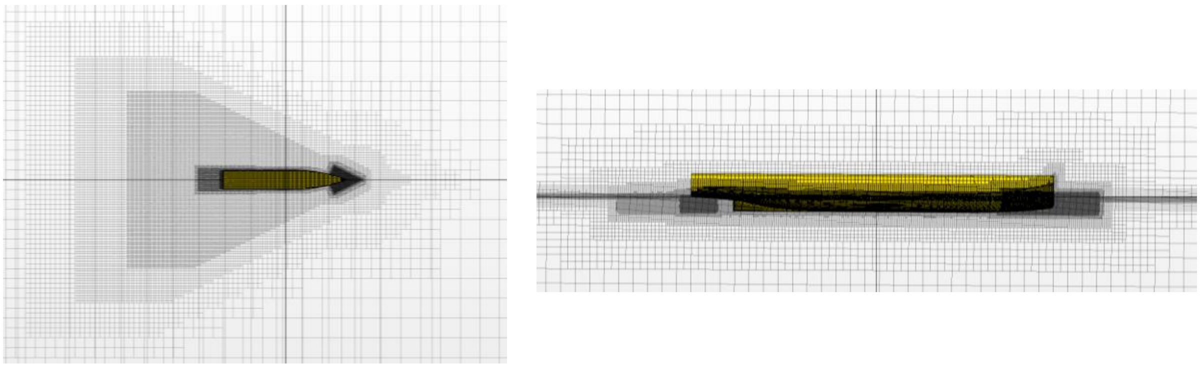

Figure 6: CFD Validation Mesh Fidelity – Plan View (Left) & Profile View (Right)

The results of the validation are presented in Figure 7. The optimisation results for Contractor 1 and Contractor 2 are within the 2% uncertainty margin, where this margin is represented by the ‘green band’ in the graph presented below.

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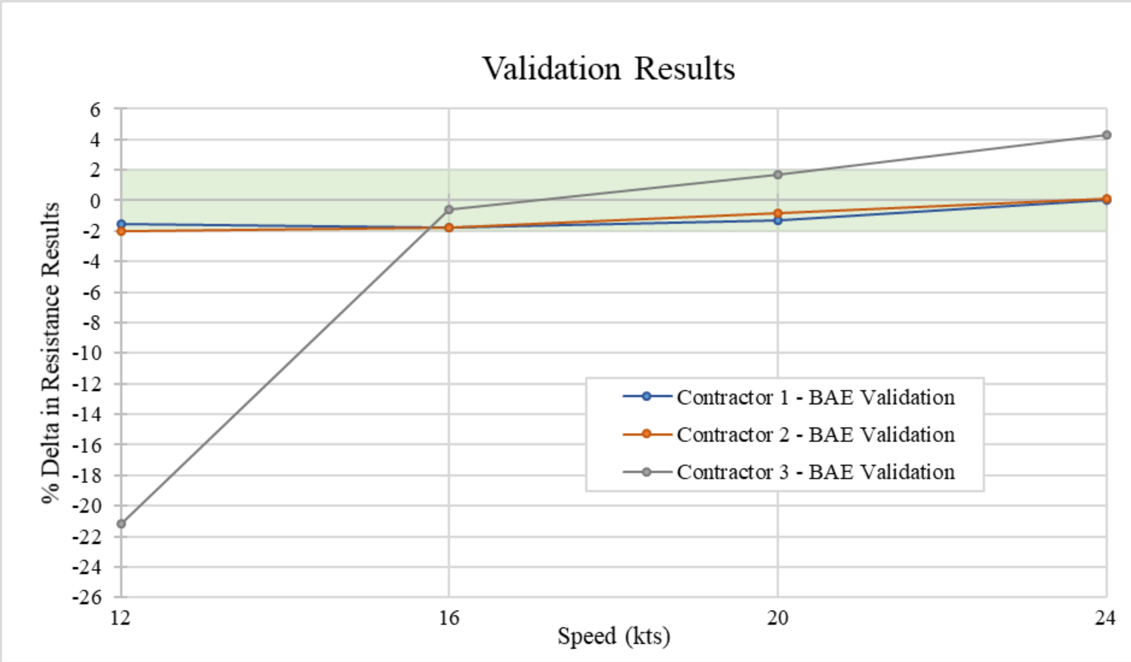

Figure 7: Validation Results for Design Condition

The average delta between the Contractor 2 results and validation is likely due to the difference in CFD software used to assess the optimised hullform. The difference between Contractor 1 and the validation is likely due to the delta in cells used in the analysis as Contractor 1 used a significantly refined mesh discretisation.

For Contractor 3, the results did not show a good correlation at lower speeds. This cannot be explained with a specific cause, however it is believed that the delta at lower speeds is likely due to a difference in the discretisation model used for the analysis. It should also be noted that Contractor 3 also used an alternative CFD software package for the analysis.

As the AI and neural networks method adopted by Contractor 2 showed the greatest average resistance reduction over the entire speed range and was the lowest scoring hullform (see Table 4), resistance model tests are being planned for mid-late 2024 to provide further validation of results.

6. Discussion

6.1 Cost

The optimisation performed by Contractors 1 and 2 was to a financial cost, whereas Contractor 3's optimisation had no associated cost due to it being an opportunity to demonstrate their optimisation software capability. The optimisation cost using the traditional approach and the AI approach were of similar magnitude.

With the optimisation software approach, although on this occasion a cost was not incurred due to it being a demonstration only, in normal circumstances there would be a yearly license fee in order to acquire and use the software package. It should be noted that in this study, an approximate cost saving of 50% would be achieved if utilising licensed in-house optimisation software rather than outsourcing the same work to a consultancy. This cost saving amplified when considering that in reality there are often multiple design projects ongoing per year within a typical ship design company.

6.2 Design Space

Due to the significant reliance on SME expertise, the manual iteration of the parametric model, and manual analysis of designs/results, the exploration of the design space was limited for the traditional method adopted by Contractor 1. Each design iteration required individual assessment and review by the SME panel before progressing to the next iteration, resulting in a time-consuming optimisation process, where the final solution is often not 'optimal' due to their being too many design parameter variables to manually iterate and explore. In total, only two design iterations from the baseline were made, both of which did not vary significantly due to the limited timeframe and budget.

This method is a reflection on the design of previous naval ships, where the data of proven hullforms was used to help inform and define future designs, resulting in a lack of design variability. The traditional method of optimisation does not facilitate the efficient exploration of the wider design space within a feasible project timescale and budget.

On the other hand, the automated optimisation approach adopted by Contractors 2 and 3 resulted in a notable variance between candidate hullforms. Whilst respecting design constraints, both the AI and optimisation software approach resulted in a number of evenly distributed hullform designs to be created within a wide design space. In particular, this was noticed by the generation of 500 hullforms by Contractor 2. This formed the training data for the neural network, where defined design parameters were assigned upper and lower bounds whilst remaining within design constraints to ensure the design space was both extensive and compliant. As a result, a significant number of compliant hullform designs could be created in a short timeframe ready to be assessed.

6.3 Barehull Resistance

Despite resulting in the same cost as Contractor 2, Contractor 1 with the traditional method produced the least efficient hullform for both the top speed condition and also across the overall speed range taking into account the operational profile for the design condition. This is reflective of the limited design space explored, with little variance between the design iterations and the baseline hullform.

Contractor 2, with the operational profile as the main focus of the optimisation across the entire speed and displacement range, produced the greatest reduction in barehull resistance across the analysed speed range.

Contrary to the approach taken by Contractors 1 and 2, the operational profile was not considered for the optimisation and solely focused on optimising for the top speed requirement for the approach taken by Contractor 3. Despite showing the greatest improvement in barehull resistance at top speed, the resistance at lower speeds in the design condition suffered as a result and lead to an increase in resistance from the baseline design. Consequently, the increase in resistance for lower speeds offset the improvement in resistance performance at higher speeds, with the results of Contractor 3 being the worst overall across the assessed speed range.

This creates a dilemma for future designs. At present, the focus is primarily on top speed requirements, not taking into account the operational profile of the ship in reality. For ship designers, this is beneficial as it will help to define the internal machinery required with the installed power and therefore informs the general arrangement. The lower resistance at top speed consequently leads to a reduction in installed power and associated systems, therefore a reduced capital cost (CapEx).

However, as shown by Contractor 3's optimisation results, the customer would suffer from a substantial penalty in terms of increased through-life costs in terms of fuel consumption (OpEx). This is proven by the fact that the ship will spend the majority of its operational life transiting at lower speeds, as presented in Figure *2*.

7. Conclusions

With the advancement of modern technology and optimisation techniques, it is evident that by using traditional methods, optimal results cannot be achieved to meet efficient fuel consumption targets while considering the limited timeframes and budgets imposed by project on ship designers.

Going forward, ship requirements should take into consideration through life costs and fuel efficiency, rather that typically aiming to maximise performance, whether this is achieved through higher sprint speeds or reduced power requirements. With the ever more prevalent need for efficient design due to the industry commitment to net-zero emissions, it is evident that moving away from the traditional approach of design optimisation is required to achieve an effective design.

Reducing the hullform resistance reduces the effective power requirement and can lead to a number of advantages to a project depending on the optimisation goals, such as improving performance, allowing for an increase in design margins (reducing risk), and/or reducing installed power (reducing cost).

In addition, using efficient optimisation techniques to reduce ship resistance leads to a reduction in emissions and environmental benefits from having a lower Energy Efficiency Design Index (EEDI); increased viability for future fuels due to the ability to store lower energy dense fuel within the same tank volume; increased range due to the lower fuel consumption, increasing the platform capability; and lower propeller loading due to a reduction in delivered power required, reducing the risk of cavitation.

Ultimately ship design should be a holistic approach, combining optimisation for multiple performance areas (resistance, stability, seakeeping, manoeuvring etc.) to ensure overall performance is improved in its entirety. By

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adopting an optimisation process using AI techniques and optimisation software, the ability is created to conduct such an optimisation in an automated way, exploring a large design space, combine performance areas, all in a feasible timeframe, all of which simply cannot be achieved using the traditional approach.

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