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A State-of-the-Art Report

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Ship Design in the Era of Digital Transition - A State-of-the-Art Report

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ABSTRACT

The evolution of ship design from a manual toward a computer-aided, digital approach has been drastic after the 1970s, with the explosive development of computer hardware and software systems. In today's era of smart digitalization in the frame of Industry 4.0, recently introduced digital/software tools and systems increase the efficiency and quality of the life-cycle ship design process, but also the operational complexity and the demand for proper training of users of software platforms. Parametric optimisation and simulation-driven design, product lifecycle management, digital twins and artificial intelligence are nowadays frequently used by the maritime industry during the commissioning/quality control activities and in the various phases of ship design, ship operation and ship production. This paper presents an overview of notable developments in the above areas and the way ahead to respond to present and future challenges of the maritime industry.

KEY WORDS

State-of-the-Art report; Ship Design Methodologies and Tools; Holistic Ship Design; Multi-objective & Parametric Optimisation; Simulation-Driven Ship Design; Product Lifecycle Management; Digital Twins; Artificial Intelligence.

PREAMBLE

The design methodology (DM) state-of-the-art reports (DM-SoA) are inherent constituents of the International Marine Design Conference (IMDC) and its long history. A synopsis of the DM-SoA timeline from the start of the IM(S)DC until 2018 was given by Andrews et al (2018) at the 13th IMDC, held in Helsinki. This timeline shows a large variety of interpretations of what the SoA report at the IMDC should or rather could comprise, ranging from reviews of the ship design history, different variants of "Design-for-X" (Papanikolaou et al, 2009, Andrews et al., 2012), as well as challenges related to the design of particular ship types.

Recognizing the importance of the DM-SoA as a binding thread between the tri-annual IMDC conferences, and the so far lack of a clear consensus on style, form and structure, the last SoA report (Erikstad & Lagemann, 2022) has more clearly formulated the goals and purpose of the DM-SoA reports, namely to "*analyze and summarize, on behalf of the marine systems design community, the current state and key developments within our field, based on a review of current research and technology achievements, as well as feedback from academia and industry*". *Regarding form, style and structure, a set of characteristics was proposed. It should be focused on marine systems design, with a clear emphasis on design methodology within the larger*

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framework of engineering design/systems design. It should be contemporary, giving priority to what have been key topic areas and achievements since the last conference, as well as ongoing research developments towards the next venue. It should be opinionated, to the extent that the authors of the report need to make an educated prioritization of what are the most important developments, as well as provide a basis for discussions and comments at the conference. Finally, it should also balance the focus between academia and industry and look into how research and technology developments are adopted in industry and actual design practice.

In this year's DM-SoA paper, we have aimed at following up on these principles. The focus will be on recent and emerging developments as well as on state-of-the-art, mature and *smart* ship design methodologies in the frame of *smart digitalization of the maritime industry (Industry 4.0)*. Parametric optimisation and simulation-driven ship design, ship product lifecycle management, digital twins and artificial intelligence are nowadays frequently used by the maritime industry during the commissioning/quality control of marine products and in the various phases of life-cycle ship design, ship operation, ship production and decommissioning/scrapping. This paper presents an overview of notable developments in the above areas and the way ahead to respond to the present and future challenges of the maritime industry.

INTRODUCTION

The evolution of ship design from a manual toward a computer-aided, digital approach has been drastic after the 70s, with the explosive development of computer hardware and software systems. In today's era of smart digitalization in the frame of Industry 4.0, recently introduced digital/software tools and systems increase the efficiency and quality of the life-cycle ship design process, but also the operational complexity and the demand for proper training of users of software platforms. It is evident that the international maritime industry and its representatives (shipping and shipbuilding industry, class societies, design companies, research institutes and academia) have widely adopted the smart digitalization concept in ship design, shipbuilding, and ship operation, long before Industry 4.0 was formally introduced, mainly in production processes. This is due to the very strong competition in the worldwide shipping and shipbuilding market. However, the degree of adoption the smart digitalization concept of Industry 4.0 strongly varies, depending on the size and competitiveness of the specific maritime industry and its representatives.

Typical forerunners in the introduction of smart technologies and associated digital services to the maritime industry are all major classification societies (e.g., Det Norske Veritas/DNV, 2023, Class NK, 2023, American Bureau of Shipping/ABS, 2023, Lloyds Register/LR, 2023, Bureau Veritas, 2023). The same applies to all major software vendors (e.g., NAPA, 2023, Dassault, 2023, Siemens, 2023) offering software tools for all phases (or part of) of the ship's life cycle (ship design, construction, operation). In between the end users/customers (shipyards and shipping companies) are in general the design offices/consultants, fitting the offered software tools to the needs of the end users or running specific software tools on their behalf. Of course, large shipyards and shipping companies may have their own specialists/software engineers to work directly with advanced software tools and adjust them to the needs of their companies. Finally, research institutes and academia may be in the forefront of initial developments of software tools, the marketing of which is however left to software vendors and partly class societies.

When looking at the level of digitalization, the maritime industry and particularly shipbuilding is often considered as one of the least digitally advanced industries. It is, however, important to understand the differences between digitization, digitalization and digital transformation:

- *Digitization*: is the conversion of information into a computer-readable format. A prime example of digitization in shipbuilding is moving from a drawing board to a CAD procedure or more generally, transforming a document or piece of information that was originally not in digital form into a computerized representation. With respect to ship lines, their digital form does not only serve as a digital drawing board that speeds up drafting and reduces the required time to create and modify technical drawings. This digital representation is the nucleus of all software tools dealing with ship design, production, and operation and the first step in creating a digital twin (DT). This stage of development is nowadays common in both the shipping and shipbuilding industry.
- *Digitalization*: is the use of digital technologies to optimize ship design, ship operation and business processes. It particularly refers to changes in the design work and in the way stakeholders of a maritime product engage and interact. It goes well beyond the implementation of technology for certain tasks and optimizes the global-scale performance of organizations, yielding a significant competitive advantage for them. This stage of development is nowadays quite advanced in all major shipping companies and class societies and to a lesser degree in some major shipbuilders.
- *Digital Transformation*: in the sense of Industry 4.0, it is the holistic, overall societal effect and wide-spread digitalization of the industry. It refers to the transformation of business models, socio-economic structures, legal and policy measures, organizational patterns, and so forth. The present stage of development of the maritime industry has

only a few "shining" examples of digital transformation, e.g., major class societies and shipping companies, software vendors.

There are only very few published studies on the digital transformation of the maritime industry, with emphasis on virtual prototyping and cyber security. According to Diaz (Diaz et al, 2023), "*the evolution of maritime and shipbuilding supply chains toward digital ecosystems increases operational complexity and needs reliable communication and coordination. As labor and suppliers shift to digital platforms, interconnection, information transparency, and decentralized choices become ubiquitous. In this sense, Industry 4.0 enables "smart digitalization" in these environments. Many applications exist in two distinct but interrelated areas related to shipbuilding design and shipyard operational performance. New digital tools, such as virtual prototypes and augmented reality, begin to be used in the design phases, during the commissioning/quality control activities, and for training workers and crews".* Ichimura et al (2022) rather focus on Artificial Intelligence (AI), Big Data Analytics (BDA), Cloud Computing and the Internet of Things (IoT), which are already used by the maritime industry, particularly in a variety of applications of the shipping industry. The maritime transport industry is already transitioning into a new operations paradigm, often termed as *"shipping in the era of digitalization".* Shipping companies promote digitalization as the future of the maritime industry and their efforts to set up strategies are already in progress. Examining those visions and strategies in relation to digitalization would be beneficial to better understand the way towards which the maritime industry is heading.

Turning to *smart* ship design methodologies and independently of a variety of professional software tools addressing main parts and specific aspects of ship design, the recently completed Horizon 2020 European Research project – HOLISHIP – Holistic Optimisation of Ship Design and Operation for Life Cycle (2016-2020) (Papanikolaou et al, 2022), in which 40 major representatives of the European Maritime industry participated (http://www.holiship.eu/), introduced an innovative, holistic approach to ship design and the development of integrated design software platforms and tools, which were used by the European maritime industry in a series of practical applications (demonstration studies). In the era of the 4th industrial revolution, the project set out to substantially advance ship design by the introduction of a fully computerized, multi-disciplinary optimisation approach to ship design and life-cycle operation. The approach enables the exploration of the huge design space in relatively short time, the distributed/multi-site working and the virtual reality testing, thus it is a strong asset for the development of innovative maritime concepts in response to the needs of the 21st century. The HOLISHIP approach is based on an open architecture scheme and the buildup of flexible s/w platforms (like CAESES®) with simple communication protocols and a long list of integrated external s/w tools. This includes, also, communication with professional naval architectural s/w platforms (like NAPA®) and interchange of data through macros. A comparison of the conventional ship design approach with a contemporary, fully computerized design procedure, as implemented in the HOLISHIP project, is shown in Figure 1, reproduced from (Papanikolaou, 2022).

Criterion	**Conventional**	**HOLISHIP**
Concept design	Empirical approach; supported by available computer-added calculation and graphics processing procedures, manual generation of 1…3 variants of baseline design and intuitive selection of the most promising variant	Automated parametric generation of hundreds of variants (*digital siblings*; cloning) and comparison to baseline design, including their documentation; *global optimisation* of main ship dimensions and main characteristics; rational (mathematical) identification of most promising variants on the basis of set criteria
Preliminary/ Contract design	Sequential processing of design steps (design spiral); individual optimisation of design properties (hydrodynamics, structures, machinery, economics) of just a few design variants	Parallel processing of design steps and design synthesis; multi-objective and multi-disciplinary optimisation of several/hundreds of design variants; local hull form optimisation
Accuracy of calculation methods	Low at concept design level (mostly empirical modelling); high at contract design level	High at any design level depending on the capability of the employed s/w tools; use of surrogate models for intensive calculation tasks
Design lead time and person months effort	*Assuming the availability of a baseline design*: Concept design: some person days, depending on the experience of the design team Contract design: several person months, depending on the experience of the design team *If no baseline is available*: Concept design: many person days of collecting information, identifying and analyzing similar ships already built from public data	*Assuming the availability of suitable parametric models*, e.g. from a previous design campaign: Concept and contract design: lead times are significantly reduced by a factor > 5 (est.); smaller design team with less need for experience of all team members *If no parametric models are at hand*:

		Several days to weeks for building up robust and meaningful parametric models, depends on modeler's experience
Costs	The effect of design variants on cost is done at early design stage intuitively by designer's experience or at best by checking the costs of only a few design variants	Early assessment of the effect of hundreds of design variants on cost leads to significant cost reductions in the production cost (CAPEX) and operational cost (OPEX) or maximization of the Net Present Value (NPV)
Quality of design (concept and contract)	Highly depend on the designer's and yards' experience	Superior quality thanks to systematic optimisation and selection of the best out of hundreds of variants; consolidated standard design documentation; Quality assurance via consistency in the assessment of variants
Safety of ship & the marine environment	Rules-based design with undefined safety level	Risk-based design with quantifiable risk consequences and safety level
Energy efficiency	Studies on energy efficiency are commonly done at contract design stage and mostly refer to the hull-propeller interaction; individual studies on overall energy consumption are nowadays common for high energy consumers (passenger ships, high-powered, special type of ships)	Improved energy efficiency in view of the integration of s/w tools for the simulation of energy consumption, including the machinery-propeller-hull interaction at early design stage
Life-cycle Performance and Assessment	Mostly restricted to the economics of an investment (shipowner's side); environmental impact is only considered by enforced regulations (considering the set IMO targets as constraints)	Life-cycle assessment and optimisation of economics and environmental impact at early design stage
Innovations in ship design	Limited, due to the lack of baseline designs to build upon	Enabled in view of the simulation-based (first principles) ship design approach; main design problem issue: definition of parametric model (transfer of innovation idea to a mathematical model)
Software platforms	Professional naval architectural software platforms with limited or no collaboration with external software tools; strict communication protocols	Flexible s/w platforms with simple communication protocols; long list of integrated external s/w tools, including communication with professional naval architectural platforms (CAESES); interchange of data with NAPA® through macros
Design workflow procedures	In general, manual planning of design workflow, which depends on designer's experience; limited coded design workflow procedures	Enables coding of design workflow procedures by macros; HOLISHIP demonstrated more than ten (9+3) coded design procedures for several ship types and marine assets
Distributed working/cloud communication	Not known in ship design	Enabled through cloud communication (IoT) and demonstrated through the RCE/CAESES HOLISHIP platforms
Virtual prototyping	Not known/limited in ship design	Demonstrated by simulation of the maneuverability of a ship with alternative rudders on MARIN's bridge simulator and feedback by the captain (man-machine interaction)
Acceptance by industry	Trivial, as conventional	At present the acceptance is limited to the HOLISHIP partners and knowledgeable academia; growing acceptance; education of future naval architects is essential; HOLISHIP book and dissemination through partnership

Figure 1: Conventional vs. an Advanced, Holistic Approach to Ship Design (Papanikolaou, 2022)

The present paper aims at an overview of notable, recent developments in methodologies of *smart ship design and operation* and a description of the way ahead to respond to present and future challenges of the maritime industry. It has a particular focus on the impact of the digital transformation on ship design methodologies, as of the remit of IMDC, but extending on ship production and ship operation with applications nowadays common to the maritime industry. After a brief introduction, Apostolos Papanikolaou presents an advanced parametric ship design optimisation, as implemented in project HOLISHIP, its historical development, and applications. Stefan Harries deals next with simulation-driven ship design (SDSD), what is closely related to ship design optimisation and the HOLISHIP project. Stein Ove Erikstad elaborates on the impact of digitalization on ship production and life cycle management. Austin Kana presents an overview of recent developments in the field of digital twins (DT) in the design and retrofit of ships and last, but not least, Evangelos Boulougouris presents methods and tools of Artificial Intelligence (AI) with applications in ship design and operation.

PARAMETRIC SHIP DESIGN OPTIMISATION

Ship Design Optimisation

Inherent to design is design optimisation, namely the identification of the best out of all feasible solutions for a set design problem. The progress in ship design optimisation in the last five decades has been revolutionary and in line with developments in hardware and software, moving from a single-objective optimisation for the minimum required freight rate (RFR) of a tanker (Nowacki et al, 1970), to multi-objective ship design optimisation of various types of ships for a variety of criteria and constraints (Figures 2 and 3).

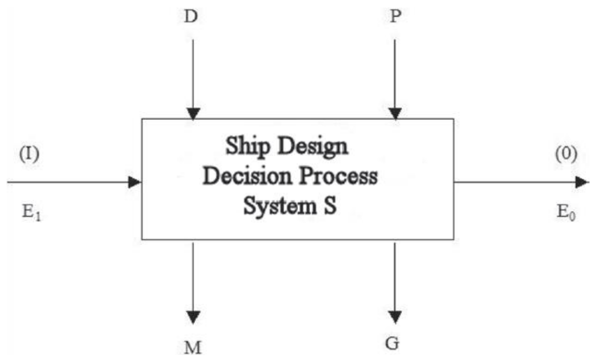


Figure 2: Single Objective Ship Design Optimisation for RFR (M: merit function, D: design variables, P: parameters, G: constraints) (Nowacki et al., 1970)

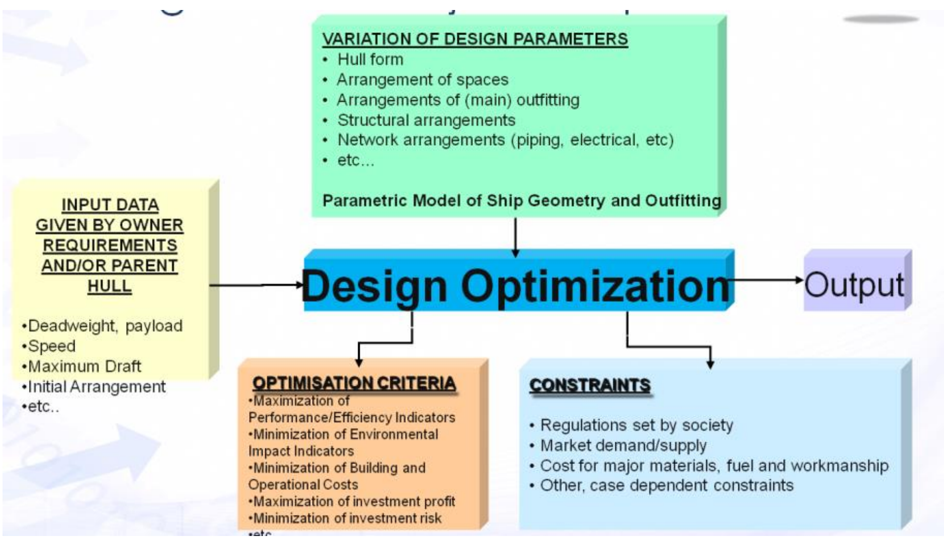


Figure 3: Multi-objective Ship Design Optimisation for multiple criteria (Papanikolaou, 2010)

The holistic approach to ship design and multi-objective ship design optimisation was introduced by A. Papanikolaou in a Special Issue of Journal CAD, which was dedicated to the 75th birthday of Professor Horst Nowacki (Papanikolaou, 2010). The outlined approach was later implemented in the EU funded project HOLISHIP (2016-2020).

Parametric Modelling - Digital Siblings

An important feature of the multi-objective optimisation procedure presented in Figure 3 is the *Parametric Ship Modelling*, namely the systematic variation of design parameters for the generation of digital "siblings". This generally refers to the variation of ship's geometry (e.g., of the wetted hull form, Figure 4), of main internal spaces (e.g., for a RoPax, Figure 5), of main structural elements (e.g., for a RoPax design, Figure 6), of ship's machinery/propulsion and main outfitting arrangements, as necessary for the processing of selected design parameters that are optimised in the frame of a defined optimisation procedure.

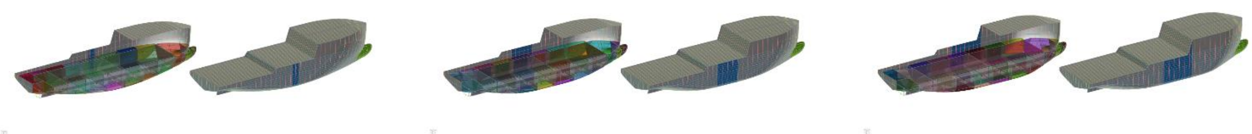


Figure 4: Three hull forms with lengthened and shortened *parallel mid-body* (shown in blue) but *identical displacement* and *longitudinal centers of buoyancy* by CAESES® (Courtesy Claus Abt, Friendship Systems, 2023)

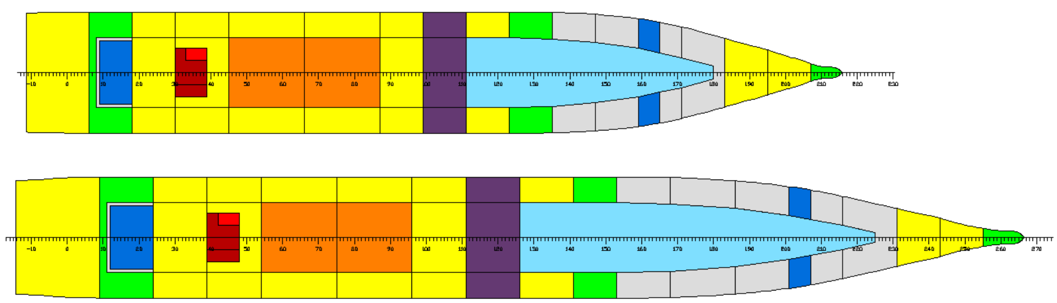


Figure 5: Internal subdivision for two RoPax hulls of different length, but identical arrangement of spaces concept, for damage stability calculation and assessment by NAPA® (Zaraphonitis et al., 2012, project HOLISHIP) Top layout for LBP=170m, bottom layout for LBP=210m.

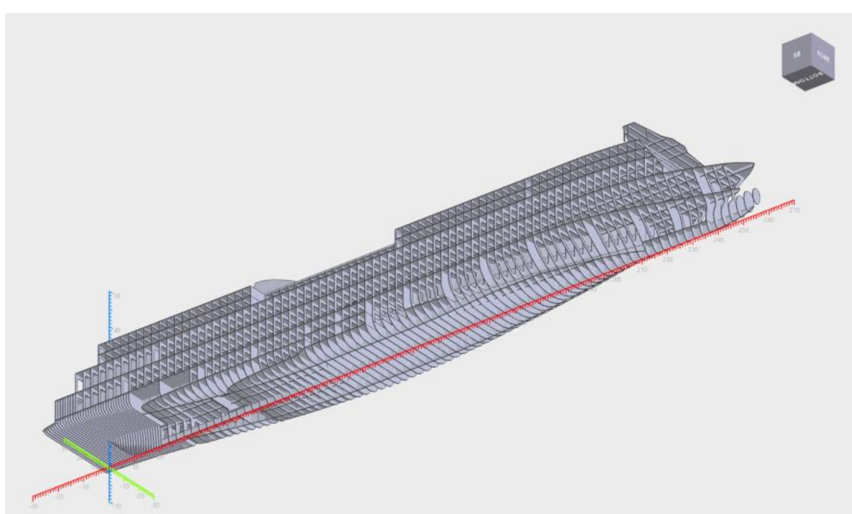


Figure 6: Parametric structural design of RoPax by NAPA Steel® (Basic model, Tuzcu et al., 2021, project HOLISHIP)

Historically and conceptually, the *parametric* optimisation of ship design was introduced by Murphy et al. (1965), when varying ship's main dimensions by systematic permutation within a certain range and identifying manually (graphically at that time) the best variant corresponding to the ship *of lowest cost*. A few years later, Nowacki et al. (1970) applied also parametric modelling by the variation of ship's main dimensions and form parameters to the optimisation of a tanker design to find the variant with the minimum required freight rate (RFR), while solving the ensuing optimisation problem by a Tangent Search Algorithm (TSA). It took about 10 years for the parametric modelling to be formally introduced into the hydrodynamic optimisation of ships by *variation of ship's hull form*, next to ship's main dimensions, in the frame of a *continuous function optimisation*. This was first applied to slender ship hull forms (mathematical hull forms, e.g., SWATH-like forms) by Kusaka et al. (1980), Salvesen et al. (1985), Papanikolaou & Nowacki et al. (1989), Papanikolaou & Androulakakis (1991) and it was later extended to a wider range of slender, high-speed vessels (Papanikolaou et al. 1996, Zaraphonitis et al., 2003). Applications to a wider class of conventional ship hull forms were first shown by Harries (1998).

The parametric modelling refers in general not only to the variation of a ship's wetted surface geometry, when dealing with hydrodynamic optimisation, but also to the internal subdivision and space arrangements of ships, when dealing with ship's damage stability of RoPax ships (Boulougouris-Papanikolaou-Zaraphonitis, 2004), while also including the parametrization of main structural elements (Tuzcu et al., 2021), or when dealing with the probability of oil-outflow of damaged tankers (Figure 7), etc. Thus, it covers both continuous, integer and discrete optimisation problems and associated techniques. It depends on the completeness of the ensuing parametric model with respect to the specific design parameters that are to be optimised in the frame of a defined optimisation problem and its processing in the frame of a simulation-driven design procedure.

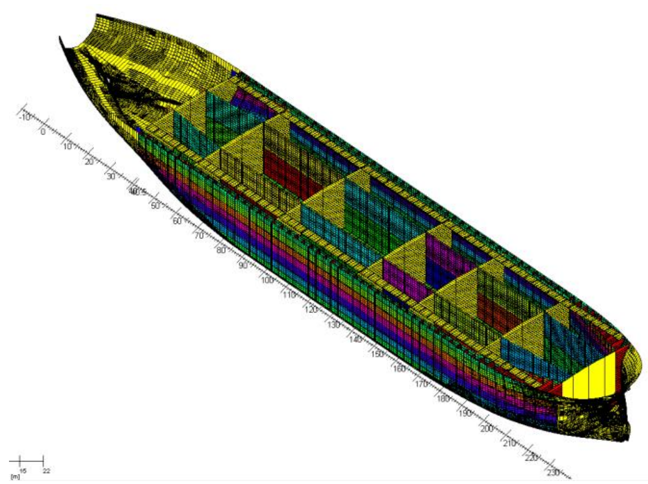


Figure 7: Parametric structural design of AFRAMAX tanker by use of POSEIDON® s/w for minimization of structural weight and of oil outflow (Papanikolaou et al, 2010, project BEST)

Parametric modelling is inherently related to *Digital Siblings*. Digital "siblings" may be seen related to digital "*twins*". However, they are of different origins and are differently used. The concept of *Digital Twin*, namely of a virtual, digital equivalent to a physical product, was introduced in 2003 by Grieves (2015). It is a virtual replica (model) of a real-world asset and it is based, besides on a digitised description of a real-world asset (here a ship), on a continuously enriched database of performance data transmitted to the virtual model from the real-world asset. This allows the virtual object to exist simultaneously with the physical one and it can be readily used in the virtual prototyping and testing of new products, e.g., in the optimisation of ship's operation after refitting a bulbous bow or of a new propulsive device; thus, it is a powerful tool of the contemporary manufacturing industry (Sharma et al., 2022, Mauro & Kana, 2022).

Digital Siblings, on the other side, are not based on the feeding with a continuous transmission of performance data of the physical asset, but are generated by the use of the design data of a *basic* digital model that is modified by systematic variation of its design parameters, *resembling the biological process of mutation, crossover and selection*. The extent of the design parameters is associated to the complexity and completeness of the ensuing parametric model that is set up by the use of a CAD software system (e.g., CAESES®, NAPA®, etc.). They should have enough modelling accuracy to allow the exploration of the huge design space in the frame of a *global* optimisation procedure, aiming at determining the object's main characteristics (Papanikolaou, 2024).

Following an advanced, conceptual/preliminary ship design approach, a ship's optimal main dimensions and main characteristics may be determined by the conduct of a properly set-up multi-stage optimisation procedure (Figure 8), as also outlined in Figure 3.

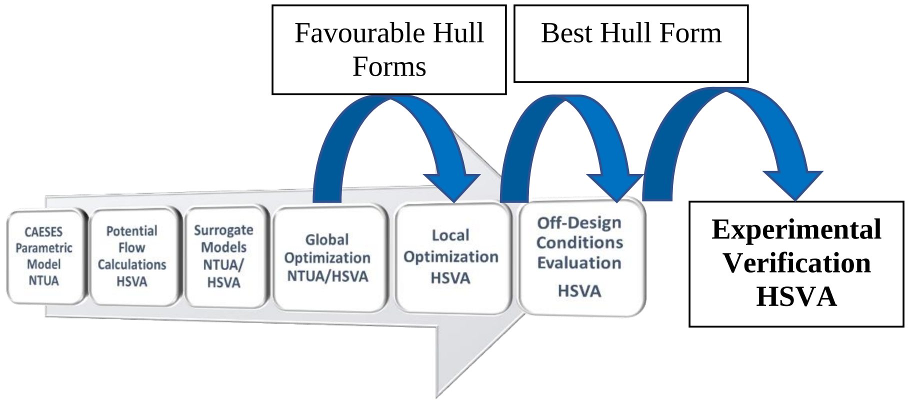


Figure 8: Multi-stage optimisation procedure applied to the hydrodynamic optimisation of a fast catamaran (project TrAM, Papanikolaou et al., 2020)

Following the *global optimisation*, in which the optimal main dimensions (length, beam, draft, and separation distance of the catamaran's demi-hulls) were identified, a *local* optimisation procedure generally follows. This can be the ship's bow (fitting or optimisation of a bulbous bow) or ship's stern or both. In the case of the optimisation of a fast catamaran, it was the transom stern region, while considering various transom stern geometries and the interaction between the ship's hull, propeller, propeller shaft, shaft-brackets and rudder (Figure 9).

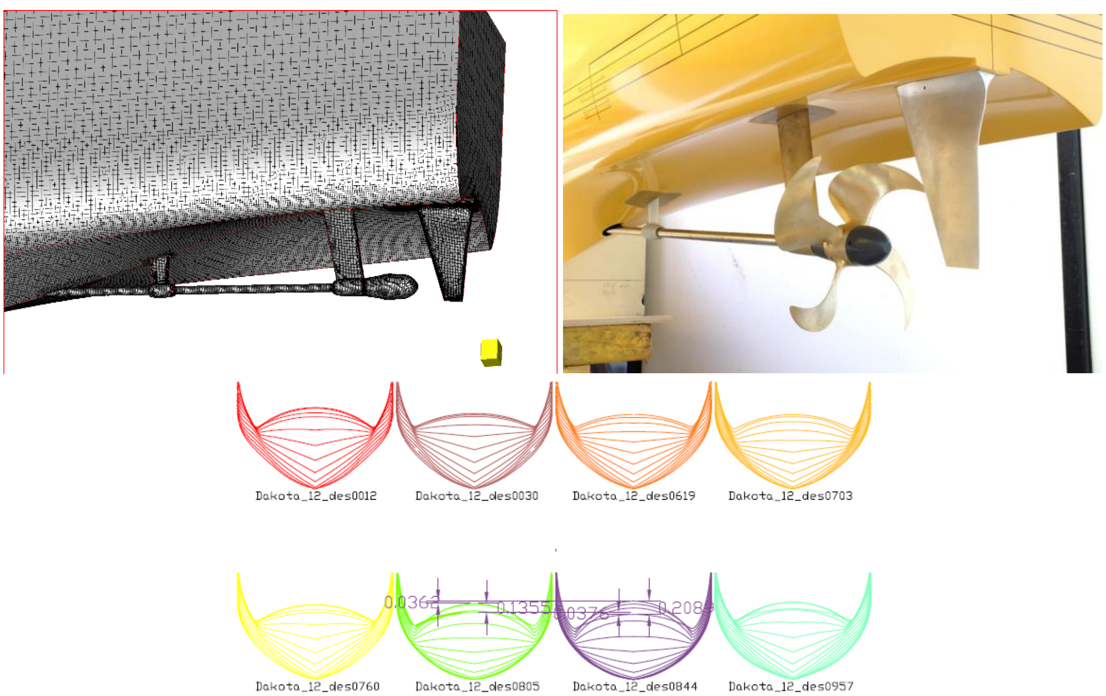


Figure 9: Local optimisation of the stern tunnel area of the Stavanger Demonstrator (catamaran *Medstraum*) by use of FreSCo+ (5.7M) - Project TrAM (Xing-Kaeding & Papanikolaou, 2021)

Because large sets of design variants need to be generated and independently assessed by partly computer-intensive procedures (e.g., CFD calculations) to determine their performance, Designs-of-Experiments (DoE), such as a SOBOL or a Latin hypercube sampling technique, are being utilized to generate variants for pre-selected free variables; the superset of all free variables representing the design space for the design task is used to generate *surrogates* of the directly calculated models. For surrogate modelling, different techniques are available such as kriging, artificial neural network analysis and polynomial regression (Harries & Abt, 2019).

Application / Demonstration Study

A variety of application case studies, which were developed in the frame of the HOLISHIP and earlier projects, are presented in details in the co-authored book Papanikolaou (ed.) (2021). A typical representative of these studies is briefly elaborated in the following. It refers to the multi-objective optimization of the design of a RoPax ship, assumed to operate between the ports of Patras (Greece) and Ancona (Italy), with a route length of 520 nm. The vessel's capacity has been specified by the end user, Tritec Marine. The service speed should be 24 knots at design draught, even keel and in deep water, with a 15% sea margin and with the main engines operating in the region of 85% MCR. The ship will be operated for 30 years, and at the end of this period, it is assumed to be sold at a value of 15% of its CAPEX.

For this optimization study of the RoPax vessel, the parametric models developed in HOLISHIP have been applied. The parametric model for the elaboration of the hullform was created in CAESES®, while the parametric models for the internal layout (the watertight subdivision and the internal arrangement of the upper decks) and for the structural arrangement were developed in NAPA® (Figures 6 and 7).

The adopted optimisation process is outlined in Figure 10.

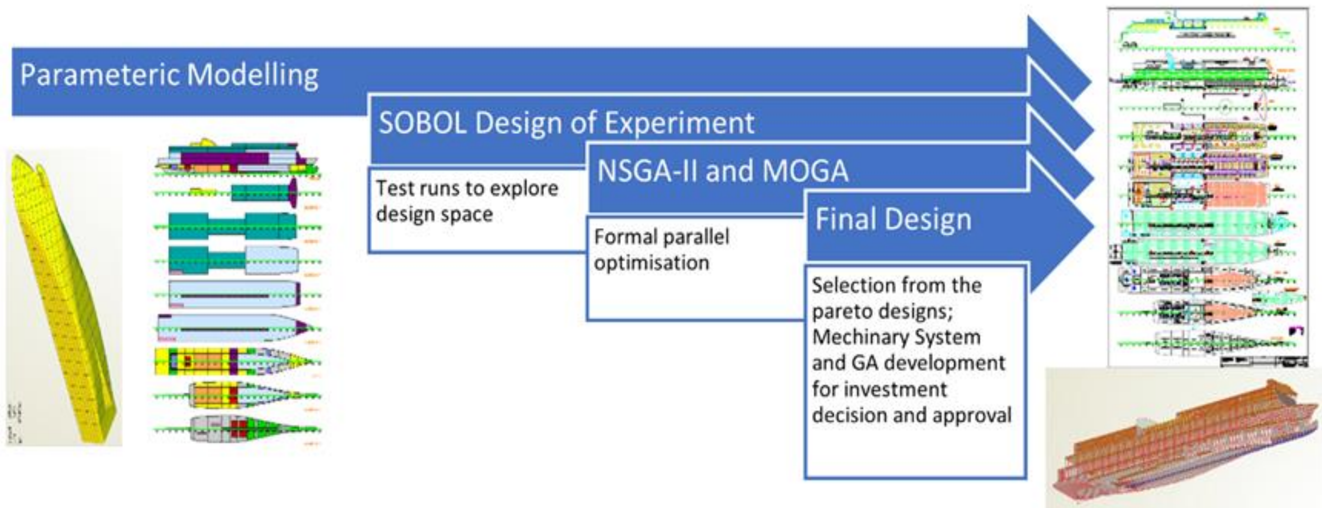


Figure 10: RoPax Optimisation Process (project TrAM)

The minimization of the payback period was selected as the objective of the optimisation, as it is a comprehensive Key-Performance Indicator (KPI), which takes into account the CAPEX as well as the yearly earnings and expenses. The implemented, most important constraints were related to intact and damage stability regulations and the EEDI requirements. With respect to the probabilistic damage stability, the Attained Subdivision Index should be greater than the Required Index by a margin of 0.01. In addition, each Partial Attained Index should be larger than 90% of the Required Index by the same margin. The attained EEDI should be less than the required Phase 2 EEDI by at least 0.2 g/tm. This is a modest requirement from the operator's point of view, presently not addressing yet Phase 3 requirements until the preferred green fuel option has been clarified.

As a first step, before the formal optimization, a Design-of-Experiment was carried out to identify significant correlations (or lack thereof) between the variables of interest within the design space, in addition to verifying the robustness of the parametric models. To this end, the well-known SOBOL algorithm was used for a total of 450 designs. Main design variables were varied within the limits, specified in Table 1.

Table 1: Design variables of RoPax Case Study (project HOLISHIP)

Design variable	Lower limit	Upper limit
Length PP	170 m	210 m
Beam	26.0 m	28.5 m
Depth to deck 3	9.0 m	9.4 m
Block coefficient	0.58	0.62

Next, a formal, global optimization for the ship's main dimensions was carried out. Two runs were conducted in parallel, one with the Non-Dominated Sorting Genetic Algorithm (NSGA-II, Deb et al., 2002) and another using the Dakota toolkit (https://dakota.sandia.gov/), which is embedded within CAESES® and uses the Multi-Objective Genetic Algorithm (MOGA) algorithm. A total of 3,000 designs were generated and assessed on top of the 450 generated during the DoE.

Typical results of the conducted multi-objective optimisation while considering 3,000 design siblings are shown in Figure 11 and the best ones with respect to specific predefined objectives and criteria were identified. The payback period of investment is about 13 years for a ship with a length of about 190m.

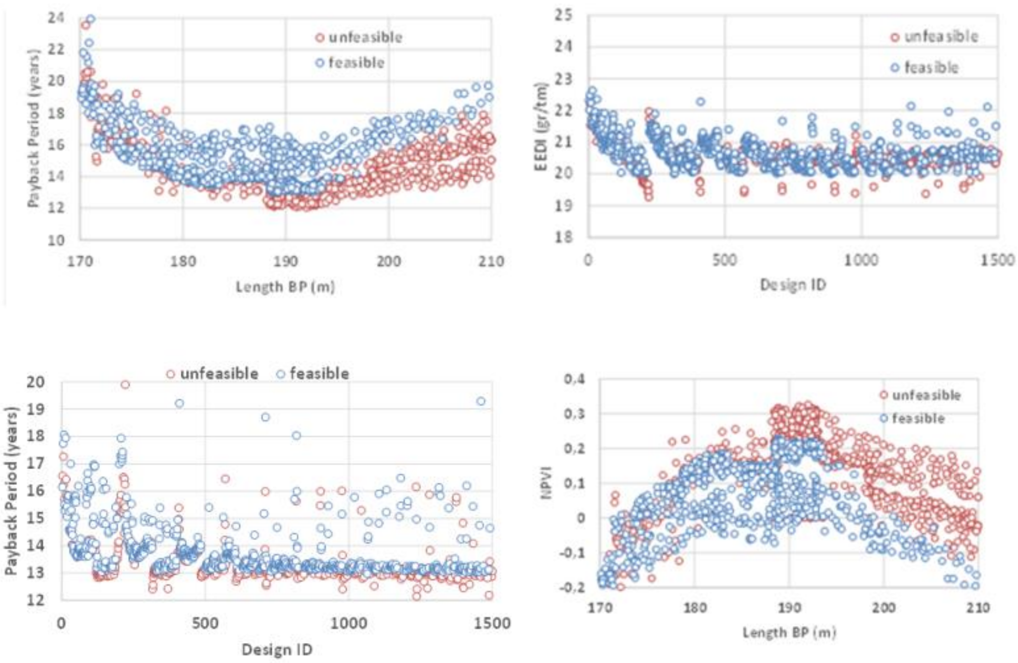


Figure 11: Sample of results of RoPax Optimisation (Project HOLISHIP)
Economic (payback period and NPVI) and Environmental Impact Indicators (EEDI)

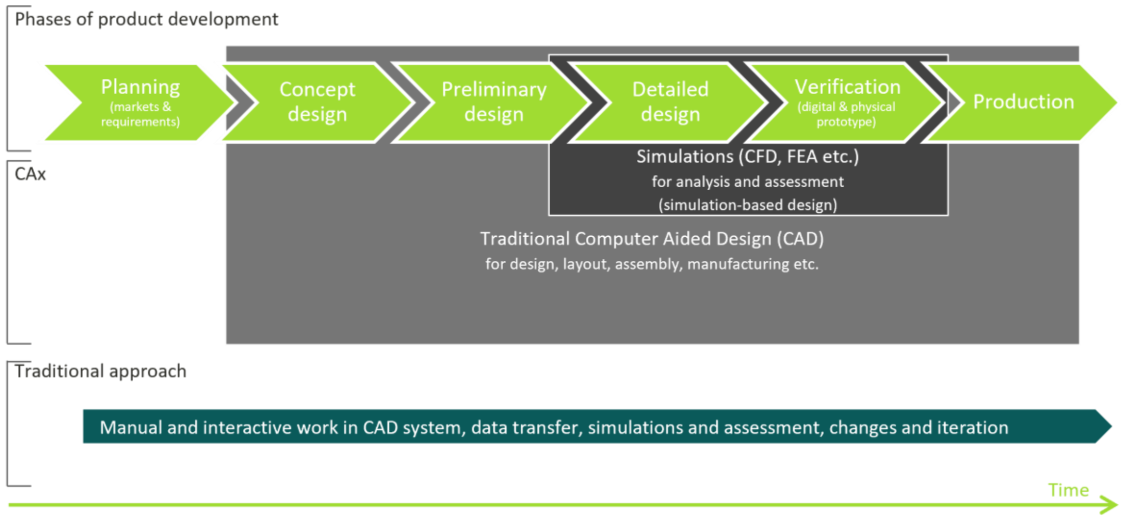
The Net Present Value Index (NPV/investment) is about 22%. The Energy Efficiency Design Index (EEDI) converges to about 20 gr/ton-miles. Optimisation studies with respect to more objective functions and other ship types can be found in the co-authored book of Papanikolaou (ed.) (2021), further illustrating the potential of holistic and formal design optimisation.

SIMULATION-DRIVEN SHIP DESIGN (SDD)

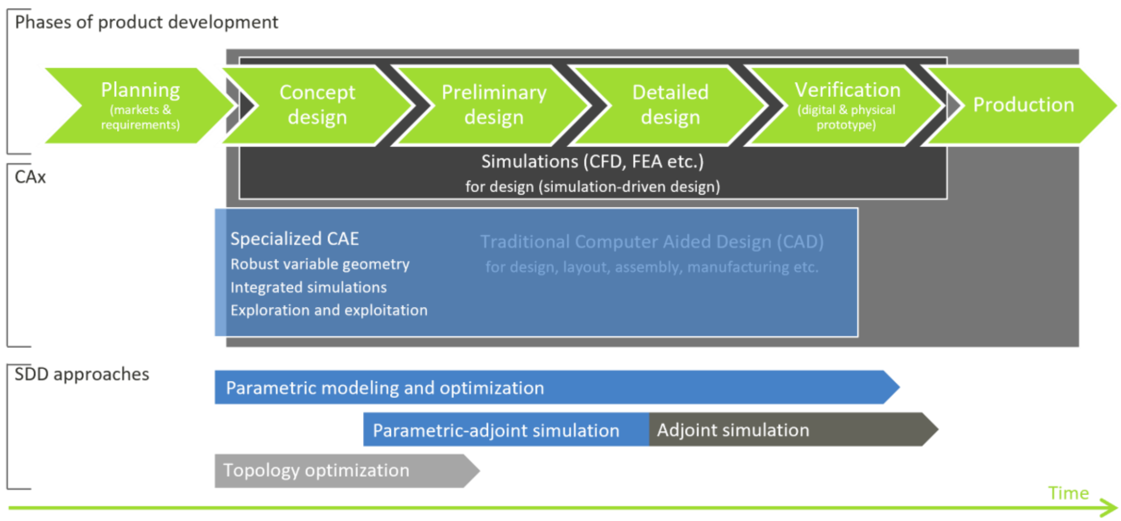
Introduction to SDD

Over the last two decades, simulation-driven ship design has gained considerable momentum and is now used at different levels as well as at various phases, from globally scanning promising candidates early on to fine-tuning specific components just before a design freeze. While the previous section gave an introduction and an overview along with an elaboration of holistic simulation-driven ship design, taking into account different disciplines, this section will give further details, focusing on hydrodynamics as a decisive element. Let us start with a definition and a clarification:

According to Funke and Jonsson (2019) "*simulation-driven design (SDD) is an approach where simulations are performed throughout the entire design process with the intention to explore options and guide the user, as opposed to just verify or falsify a design in the later stages of the process.*" This means that simulations are utilized to actively bring about design variants, shifting the usage of simulations from late cycles towards the front, see Figure 12, while enriching the set of proposals that design teams would typically come up with by traditionally combining their specific knowledge, experience and creativity (see also Figure 1).



(A) Traditional design approach, using simulation-based design



(B) Simulation-driven design, complementing the traditional approach

Figure 12: Phases of product development and utilization of simulations

While manual design work rarely surpasses the creation and analysis of more than a handful of options, SDD typically results in many variants, often several dozens and sometimes hundreds or even thousands, see section above. Clearly, this differs from simulation-based design (SBD) in which just one or several rather mature designs undergo some selected simulations to ensure sufficient performance or to identify problems to be mitigated manually within another design iteration. Figure 12 (A) and (B) illustrate differences between the traditional approach and the various SDD approaches available so far. It should be noted that SDD does not replace traditional design as such but rather complements it. (In this sense Figure 12 (B) can be seen as an overlay to Figure 12 (A).)

Traditional design is typically built on using one or combining several CAx systems. Geometry is created interactively by means of Computer Aided Design (CAD), introducing parameters while doing so. Components and systems are added and assemblies are established step by step, making changes increasingly tedious and expensive to realize. The CAD systems employed mostly originate from a time in which computer resources and simulation tools were not yet advanced enough to incorporate sophisticated simulations – e.g., Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD) and, in ship design, damage stability analyses – tightly and at an early stage.

Many of today's CAD systems were production-oriented when started, see Harries et al. (2015), and most follow a history-based modelling approach in which the interactive modelling steps taken by the user are "recorded." The systems are very powerful and many of them now cover several if not all phases of product development. However, they frequently fail to regenerate shapes readily when several input parameters are changed at a time and the history-based model is replayed for an update. Failures can be fixed interactively by the CAD user but any need of manual interference hinders the creation of large sets of variants as is representative of SDD.

The previous section of this paper describes how preliminary design can benefit from SDD by building synthesis models, and partially replacing expensive simulations with surrogates. In preliminary design, the focus is to identify the main dimensions and to find the best topology for the expected operational profile. The purpose is to make the right decision globally. Once the concept and the preliminary design are established SDD comes into play again with the aim of improving the product even further. Within this section, this local application of SDD shall be explained in more detail. Special attention is given to hydrodynamics as a key for energy-efficient operations. On most commercial ships resistance and propulsion account for more than two thirds of energy consumption, see for instance Harries et al. (2023).

As done in preliminary design and at a global level, the overwhelming majority of SDD applications at local level are built on parameters. Parameters are meaningful descriptors of a product that can be addressed and, interpreted as free variables, modified during the development process, see Harries et al. (2015) and Harries (2020). As shown in Figure 12 (B) there are parameter-free approaches like topology optimization and adjoint simulations, too.[1] However, they are not easily applied in multi-objective or even multi-disciplinary optimization campaigns while parametric modelling readily allows mixing objectives and disciplines by creating supersets of free variables from the various parametric models.

Since simulation results form an essential part of the SDD process there is one decisive prerequisite: The simulation(s) employed need to be good enough to ensure the correct ranking of variants. While high absolute accuracy is desirable it is often sufficient that the simulations yield correct relative accuracy. If that was not the case SDD would very likely mislead the design team. Therefore, before engaging SDD it is critical to ensure that an improvement found in a simulation would also materialize in real life.

In ship hydrodynamics, this has been regularly done by comparing simulation results with measurements from model tests. However, an additional challenge is that results at model scale, particularly for energy-saving devices attached to the aftbody, are not easily transferable to full-scale. Moreover, not many full-scale measurements are available but for a recent industry initiative, see Ponkratov (2023) and https://jores.net, to provide suitable benchmarks. For direct comparisons between two ships that are identical except for only one design element there is even less data to be found. Çelik et al. (2022) reported sea trials in which a conventional rudder was compared to a Gate rudder system that had been optimized using SDD, see Gürkan et al. (2023).

Let us assume for the sake of discussing SDD further that the chosen simulations are good enough. This has been the situation in several industries for quite some time, e.g., for selected applications in naval architecture like optimization of calm-water resistance and propulsion, in turbo-machinery for increasing efficiency and operating range as well as in automotive and engine design for better aerodynamics and cleaner combustion, respectively.[2]

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[1] In topology optimization – sometimes also referred to as generative design – a volume is provided that is sequentially filled with material, for example, to find a light-weight structure for clearly known load cases. While this is applied for the design of components it has not become popular (yet) for the large structures that ships and even boats are made of. In fluiddynamics topology optimization is used to identify meaningful flow paths within enclosed spaces for which inlets and outlets are prescribed. The available space is iteratively filled up, constricting the fluid domain, until an objective is minimized, e.g., pressure drop. Again, this is rather done for internal flows at component level.

In adjoint simulations some of the boundaries of a geometry to be optimized are considered to be free to change, primarily in normal direction to the original shape. From the adjoints so-called shape sensitivities are derived that suggest which parts of the boundary have to be pulled out and which have to pushed in so as to improve a chosen objective. This is mostly undertaken at the stage of fine-tuning an already good design as adjoint simulations inherently identifies a local optimum close to the original shape. See Harries and Abt (2019) for more details and references.

[2] Success stories have been reported by users of high-fidelity CFD codes such as ANSYS CFX, Cadence® FidelityTM CFD (formerly known as FINE/Marine), SHIPFLOW, Siemens Simcenter STAR-CMM+ and certain OpenFOAM set-ups as well as Process Integration and Design Optimization (PIDO) systems such as CAESES®, modeFRONTIER, Optimus®, and optiSLang to mention a few.

Standard Ingredients of SDD

The standard ingredients of SDD are versatile parametric models, accurate simulations, formal strategies of exploration and exploitation and, since a few years, surrogates:

- A parametric model is any model that captures the information of interest about a system within a finite set of descriptors, i.e., the parameters. This may be a product's geometric representation as needed for engineering.[3] It may also be just an empirical relationship between certain inputs and required outputs.
- Simulations are predictions of aspects of system behaviour via an approximate (mathematical) model, omitting less important characteristics. Potential flow analysis of seakeeping behaviour may serve as an example in which viscosity is neglected yet the numerical results are of sufficient practical value. RANS simulations capture viscous flows by averaging the influence of turbulence, giving a close enough account of the flow field for many design purposes.
- Exploration is the automated scanning of a design space within the bounds chosen for the free variables, i.e., a sub-set of parameters that can be controlled by the design team. The purpose is to understand correlations between inputs and outputs, to identify promising regions (for further exploitation) and to provide data for building surrogates and/or to feed machine learning. The algorithms are those of Design-of-Experiments (DoE), for instance, the quasi-random Sobol sequence, allowing repetition and extension, and Latin Hypercube sampling. An illustration from a Sobol sequence is shown in Figure 13. The idea of a DoE is to spend as few resources as possible while getting a good overview. In recent years adaptive sampling algorithms have been introduced that place additional variants where the expected error and/or lack of information is still (the) high(est).
- Surrogates are the replacement of simulations by means of approximating models, also known as meta-models and response surfaces. Polynomial regression, Kriging and Artificial Neural Networks are popular surrogates. Upon computing a surrogate, for instance, by training on data produced during exploration, the execution of a rather expensive simulation can be sidestepped. Surrogates take just split-seconds to execute but do not necessarily yield the result that the actual simulation would give, introducing additional errors. Occasionally, a supplementary simulation is run once a promising design candidate was found, checking and, if need be, improving the surrogate afterwards.
- Exploitation is the automated improvement within the chosen design space with respect to one or several objectives, observing inequality (and sometimes equality) constraints. Exploitations can be run on the basis of simulations, surrogates or a mixture of both. Depending on which algorithm is utilized, deterministic and stochastic strategies are distinguished. Popular are local optimization based on pattern search, like the Nelder-Mead Simplex due to its simplicity, and global searches via genetic algorithms, like the NSGA-II. Global strategies cover the design space widely and advance towards non-dominated variants, yielding a Pareto frontier.[4]
- Exploration, surrogates and exploitation are combined in advanced and encapsulated strategies. Here, an initial set of variants is produced and analysed via simulations from which then a first surrogate can be derived. Additional variants are produced by further populating the design space while reducing the deviation between the surrogate(s) and the underlying simulation(s).

Ingredients and benefits of SDD are also summarized by Massobrio (2023) and are elaborated in Harries (2020).

Importantly, when commencing with an SDD campaign the people involved need to get together and agree on the following: Which key performance indicator(s) should be improved (objectives) and which should be observed and complied with (constraints), what parameters are really under the control of the design team and shall be deliberately modified (free variables) and what can actually be simulated within the given time, the available resources and with acceptable accuracy. While this seems trivial at first glance it more often than not turns out to be complex and is, frequently, no subject of spontaneous agreement.

Furthermore, SDD should not be understood solely as another term for optimization. A Design-of-Experiment, for instance, helps to understand cause-and-effect, getting an appreciation of the potential for improvement and yields insight into which of the free variables are important and which could possibly be fixed subsequently to reduce the design task's dimensionality. A surrogate built from a DoE allows capturing, providing and storing expert knowledge for a certain type of simulation by summarizing results in terms of a simple mapping between inputs and outputs, e.g., saved in csv-files. A complex simulation is taken care of by the specialist with software whose license may be expensive and whose usage may require a lot of experience. This unloads the burden from the design team and may even help improve the quality of the outcome, see Harries and Abt

[3] This may well differ from a parametric model suitable for production.
[4] A Pareto frontier is formed by the set of non-dominated variants, i.e., variants which cannot be further improved with regard to one objective without deteriorating the performance of one or several other objectives at the same time.

(2019). It also paves the ground to combine various design solutions that could not be simulated concurrently, see for instance RETROFIT55 (2024) and Marzi et al (2024), albeit at the cost of neglecting mutual influences of higher order.

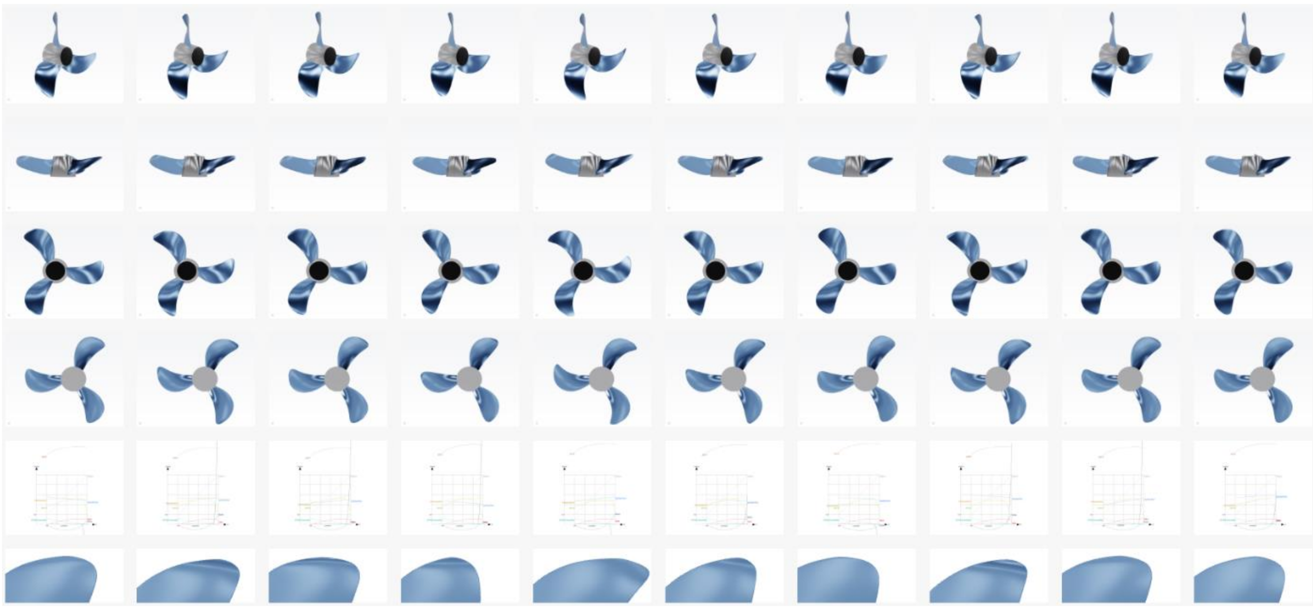


Figure 13: Excerpt from a DoE for the SDD of a propeller
(Differences can be best seen at the tip in the bottom row where various tip rakes occur)

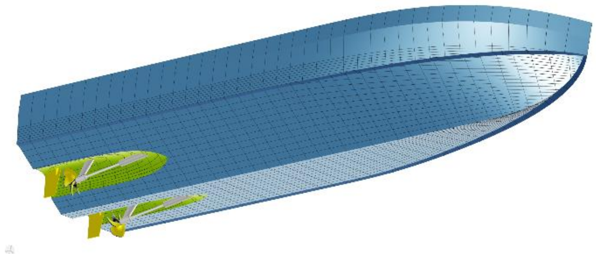
Moreover, in situations in which many components need to play together in a concerted way like in retrofitting a ship in operation – such as changing a bulbous bow, placing a wind-assistance device on deck and modifying the propeller – the behaviour of each system can be captured without the need to already know the influence of all other systems beforehand. Thus, the interdependence can be left to finding the most favourable balance at a later stage when employing the surrogates. This is not only faster but also allows replacing quickly certain components with alternatives and/or adjusting the design task to changing requirements. Additionally, it helps reduce the complexity of the design task.

Illustrating Example of SDD

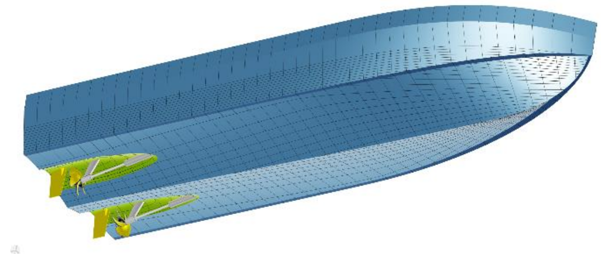
For the sake of a better appreciation let us take a closer look at a selected example: The hull form of a fast pilot boat was to be optimized for its design speed of 27.5kn at 9.5 tons of displacement. Details of the project are presented in Ahmed et al. (2023) and a thorough elaboration is given in Harries et al. (2024). Here, just the general SDD process shall be explained, see Table 2. Additional SDD examples can be found in Harries (2020), covering naval architecture, turbo-machinery and related fields of application.

Table 2: Typical SDD process

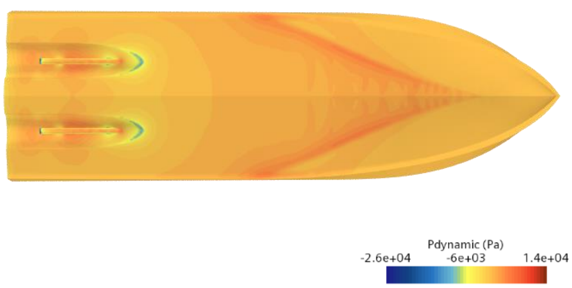
Step	General	Illustrating example
1	Discuss and define the objective(s), constraints, free variables and their bounds; decide which less important characteristics are to be omitted	The shipyard wants to build a fast monohull with conventional propulsion – diesel engine, shaft, bracket, propeller and rudder – with high energy-efficiency at 27.5kn, estimating weight to be 9.5 tons. The pilot boat is to operate in protected waters by professionals, allowing to focus on calm-water performance.
2	Build parametric model(s); balance freedom to change the design (i.e., degrees-of-freedom) with resources available (time and budget)	The hull features two propellers and tunnels for their accommodation. A parametric model, ready for simulation, is created (here in CAESES®) with eight parameters for the bare hull and ten parameters of the tunnel as free variables, see Figure 14 (A) and (B).
3	Set-up simulation(s); check the accuracy of simulation (unless already proven) and possibly reduce simulation effort per variant	Calm-water RANS simulations are set-up (here in Simcenter STAR-CCM+), see Figure 14 (C) to (F). A systematic comparison to model tests shows very good agreement for free trim and sinkage. Grid variation studies are performed to identify a compromise between accuracy and effort per variant. Appendages are found to be negligible for the optimization runs since they do not disturb the correct ranking of variants.
4	Undertake exploration; identify promising designs (and favourable regions in the design space)	Many dozens of variants are automatically generated and analysed without manual interference (hereby coupling STAR-CCM+ to CAESES® as a PIDO environment).
5	Study correlations; possibly adjust bounds and/or eliminate less important free variables	As depicted in Figure 15 thrust (see first row) as objective along with other key performance indices depends on all free variables. Some free variables have a very strong influence, e.g., lowerTransom which controls the bare hull's stern geometry (see second-to-last column in Figure 15).
6	Discuss potential for improvements; possibly redefine, swap and/or drop objectives and constraints	First improvements are found during the DoE, see Figure 16, giving an appreciation of optimization potential.
7	Build surrogate(s) and train machine-learning models	Kriging is used for a surrogate of thrust as a function of all free variables. For further machine learning (ML) see Ahmed et al. (2023). As illustrated in Figure 17 a ML model allows estimating the flow field, too.
8	Undertake exploitation directly on simulation(s) and/or on surrogate(s)	Starting from a particularly good design, i.e., variant number 15 as shown in Figure 16, two local searches, one using simulations and another using the surrogate are performed.
9	Pick promising designs; possibly repeat some of the previous steps	Various other exploitations are run (not shown here). Details can be found in Harries et al. (2024).
10	Determine performance of promising designs; refine simulation(s), study other design aspects not taken into account during the SDD campaign; possibly repeat some of the previous steps	Additional simulations with higher grid resolution, also with appendages, are run to confirm the improvements found during the optimization, see Figure 14 (C) to (F). For thrust as an objective, using an actuator model for the propeller, a reduction of about 10% could be found for the so-called 3rd optimized design when compared to the new baseline.



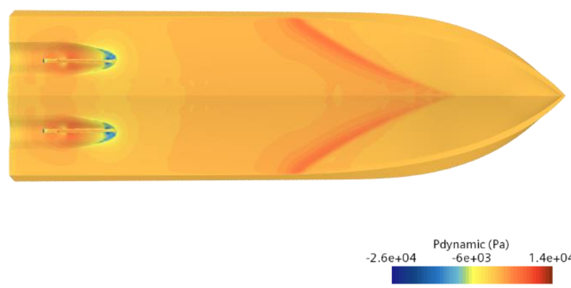
(A) New baseline



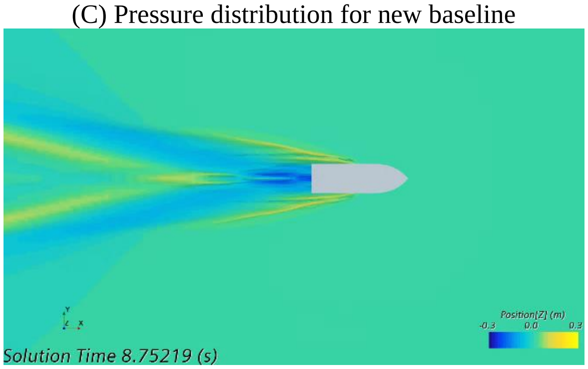
(B) 3rd optimized design



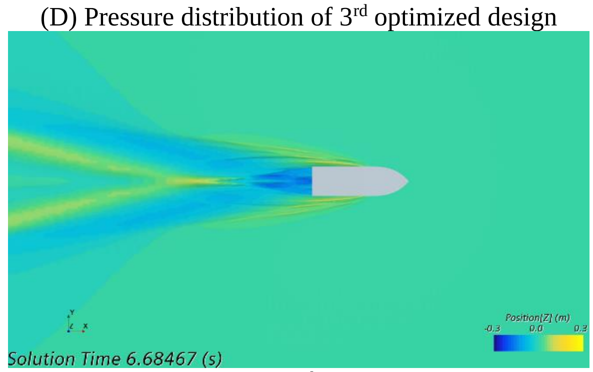
(C) Pressure distribution for new baseline



(D) Pressure distribution of 3rd optimized design



(E) Wave field of new baseline



(F) Wave field of 3rd optimized design

Figure 14: Parametric model built from assembly of bare hull, tunnel and propulsion train and associated flow fields

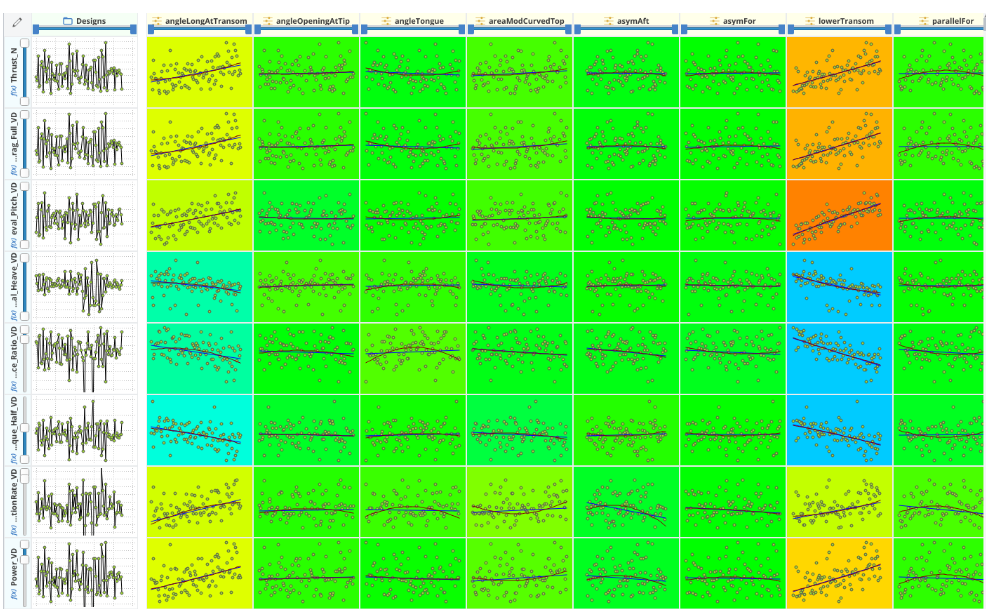


Figure 15: Excerpt of results from DoE (thrust, drag, pitch, heave etc. as functions of several free variables)

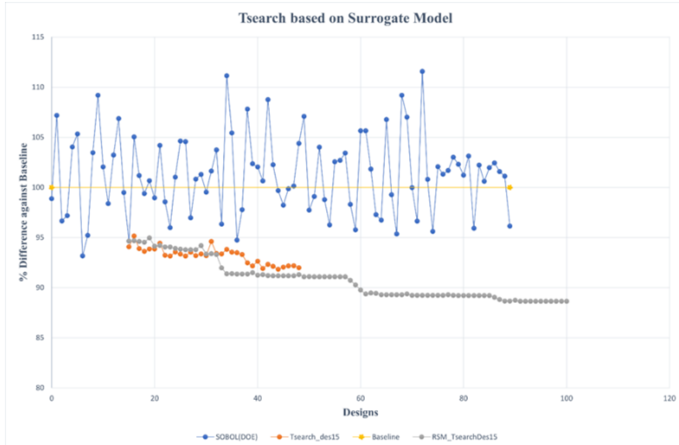


Figure 16: History of DoE and deterministic local searches run on simulation (orange) and on surrogate (grey)

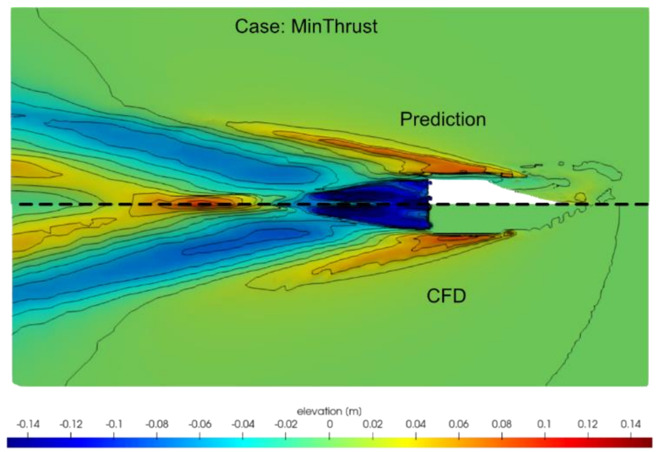


Figure 17: Wave fields for the prediction from a machine learning model (upper part) and corresponding CFD simulation (lower part) for a fast monohull giving minimum thrust

SHIP PRODUCTION AND LIFECYCLE MANAGEMENT

Lifecycle aspects of marine systems design methodology

In the previous IMDC state-of-the-art report (2022), specific lifecycle aspects were discussed under the headings of "design for sustainability" and "design for uncertainty and flexibility". The former of these now permeates every aspect of the ship and fleet development process as the industry aims towards net zero by 2050. The latter is simply a consequence of the road ahead being neither constant nor known. Since 2022 the importance of lifecycle aspects has continued and even strengthened, as well as increased in scope and complexity by the introduction of market-based mechanisms in the EU.

In this section, we will define the concept of "Design for Lifecycle" (DfLC) from the point of specific design methodology developments in various phases of the ship design process.

A pertinent question to begin with is, what is "design for lifecycle"? The 30-year-old definition by Ishii (1995) is still valid: "*Life-cycle engineering seeks to incorporate various product life-cycle values into the early stages of design. These values include functional performance, manufacturability, serviceability, and environmental impact*".

Often, this concept is tied to "Product Lifecycle Management", or PLM for short. PLM, and its sibling Product Data Management (PDM) is basically about managing all data about a product from cradle to grave. PLM is an important pre-requisite for digital twins and is a key part of what is often termed "Industry 4.0" or "Shipbuilding 4.0". However, PLM as such is not particularly about *design*, but rather how to manage the *outcome* from the design process throughout the lifecycle.

Thus, DfLC is here understood as "all activities within the overall design process that explicitly takes into account the lifecycle aspects of the ship". But do we not always design for the lifecycle? As stated in (Papanikolaou, 2019): "*One of the most important design objectives is to minimize total cost over the life cycle of the product, taking into account maintenance, refitting, renewal, manning, recycling, environmental footprint, etc*.". We typically assume a certain longevity of the vessel, say, 25 years, and this indeed drives many design parameters. Still, in the design process we need to make simplified assumptions about the operational life of the vessel. For instance, it is common to assume a fixed deployment or contract, even when there is a positive probability that the vessel will change missions. We may define a static external operating context, such as prices, fuels, technologies, regulations, etc., while in reality these are highly uncertain and vary substantially. More basically, we implicitly act as if we know and understand the future, by capturing this in a model or a set of parameters. However, while we are *always* designing for the future, the future is intrinsically uncertain, and this should be explicitly captured in a DfLC process.

Thus, a more fitting interpretation of DfLC would be "design aspects related to explicitly taking into account an extended set of design parameters that are dynamic, multi-faceted and uncertain". To cater for this, there are four distinct aspects of the design process we need to address:

1. The capturing of needs and requirements that have an impact on lifecycle value creation and compliance.
2. The appropriate modelling of the anticipated future technical, commercial, and regulatory context in which the ship or fleet is going to operate, considering that this future is both uncertain and changing.
3. The development of design solutions that are capable of delivering value and meeting stakeholder expectations throughout this changing and uncertain lifecycle.
4. Prepare for the continued management of all aspects of the ship´s future operation, bridging the gap between the ship "as-designed" and "as-operated".

Needs and requirements in a lifecycle perspective

The ship design process starts with understanding the needs and requirements of key stakeholders, (Brett and Ulstein, 2015). We have seen a gradual development towards an increased emphasis on lifecycle aspects of this step in the design process.

First, needs and requirements have become more dynamic and long term. This is a shift from a more static set of needs and requirements towards a situation with partly known and partly anticipated requirement changes along the vessel´s lifecycle, with a "license-to-operate" level of criticality. Largely, this is a consequence of the planned stepwise reduction in greenhouse gas emissions from shipping and the net zero ambitions by 2050.

With global warming at the top of the political agenda, and the IMO goal of near zero emission shipping by 2050, design-for-sustainability becomes the most important lifecycle element of the design process. For ships to be designed and delivered during the next couple of years the powering technology and fuels required for meeting the 2050 targets is simply not commercially available in the market. This implies that needs and requirements will change throughout the lifetime of the vessel (Erikstad, 2022).

The revised IMO strategy that was adopted in July 2023 calls for international shipping to achieve net zero by 2050, which is a significantly more ambitious goal than the 50% reduction that was the previous target. Along this way, there is a goal of 20% reduction by 2030, and 70% reduction by 2040. Thus, from a design perspective, we are in a somewhat new situation with explicit and changing requirements with a 25 year perspective, i.e., still within the lifespan of ships designed and built within the next few years.

In the shorter term, IMO has also adopted non-static requirements such as EEDI, EEXI, and, most recently, CII. These are all measurable index requirements that are tightened stepwise. The Energy Efficiency Design Index (EEDI) defines minimum energy efficiency level requirements for new ships, motivating for energy-efficient equipment and engines. A similar measure is the Energy Efficiency Existing Ship Index (EEXI) covering the energy efficiency of existing vessels. The more recent Carbon Intensity Indicator (CII) rates ships on a scale from A to E based on their CO_2 emissions during operations. Even if a new vessel has an adequate rating at delivery time, the gradual tightening of the CII indicator is likely to require that the vessel is retrofitted at regular times during its lifecycle. To ensure this a Ship Energy Efficiency Management Plan (SEEMP) is required for the monitoring of the ship's energy efficiency over time in order to comply with CII targets.

This focus on carbon efficiency in the short term, and zero emission for the longer perspective can also be traced to the shipowner´s fleet renewal processes. Some examples from the stated strategies of major shipowners illustrate this, e.g., "*Our ambition is to continue as a frontrunner, providing carbon-efficient freight 'right here, right now', and to enable zero-emission shipping in the medium-to long term"* (Klaveness, 2024), and "*Net zero across the business in 2040*" (Maersk, 2024).

Capturing the lifecycle operating scenario of the vessel

A prerequisite for finding preferable design solutions from a lifecycle perspective is that we are able to model the future external operating context at a level of detail sufficient for deriving relevant performance indicators for the system of interest, whether this being monetary, environmental or technical. Key players in the maritime industry have put substantial efforts into this, using a wide array of methods and strategies. One example is DNV´s annual "Energy Transition Outlook" which presents forecasts to 2050 covering renewable energy technology cost and implementation schedules, prognosis on regulatory framework and policies, fuel availability and prices, to name a few (DNV, 2023). Interestingly, DNV´s approach in this report is to present a "single best estimate" forecast of the future energy situation, based on what they call a "comprehensive system-dynamics model". Thus, this is a deterministic rather than a stochastic model, using expected value input parameters towards one particular output, corresponding to what is called a "maximum likelihood model" in risk analysis. The benefit of this is simplicity and improved transparency. One drawback is that even if this is the most likely forecast, it is still rather unlikely given the model´s complexity and the stochastic input parameters. Further, if used as part of a systems design process, the value of incorporating flexibility towards alternative, uncertain futures becomes zero for a single scenario model (de Neufville & Scholtes, 2011).

The alternative to this modelling approach is to explicitly model multiple futures as scenarios, and then evaluate a prospective design towards a (probability-weighted) distribution of the outcomes from each. There have been multiple examples of this in the maritime design literature (see Gaspar, 2012). One interesting recent example is based on the exploration of market uncertainty towards the design of offshore wind foundation installation vessels. To reduce the levelized cost of energy (LCOE), the offshore wind energy market has seen an increase in market demand, turbine size and distance from shore. According to Zwaginga (2021), "*this makes it difficult for ship designers to design a construction vessel that has the right size and capabilities for use over multiple decades.*" Designing for the first contract is likely to make a vessel increasingly less competitive over time, though how far and how fast this will go is highly uncertain. As a consequence, a large number of scenarios were generated with variations of characteristics such as range, sizes, contract types and market parameters, to be used for evaluating alternative concept designs, see Figure 18.

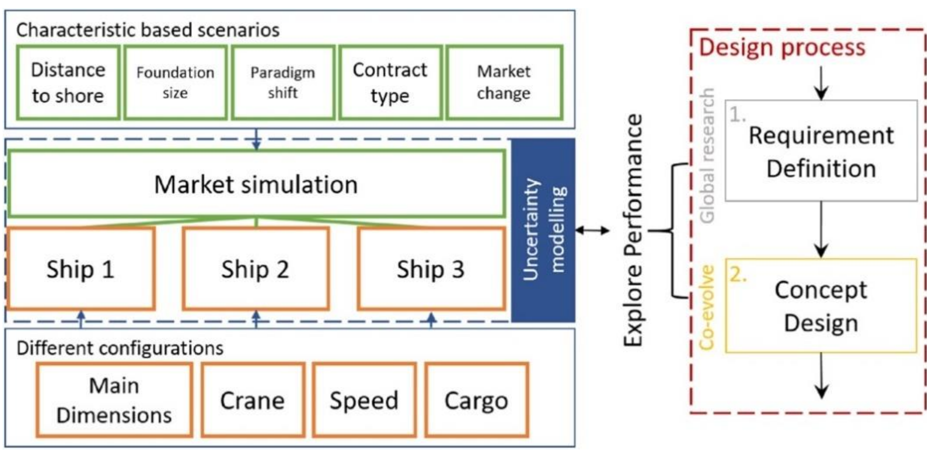


Figure 18: Scenario development for HLCV (Zwaginga et al, 2021)

Again related to lifecycle sustainability considerations, it is perhaps the uncertainty related to the availability and cost of fuel alternatives along the lifetime of the vessel that has become the most serious challenge in the conceptual design phase (Lagouvardou et al, 2023). According to DNV (2023), in order to meet the IMO GHG goals of 2030 shipping will require 30%-40% of the estimated annual global supply of carbon-neutral fuels, in competition with other sectors. Adding to complexity is the inclusion of shipping into the European Emission Trading System (ETS). In ETS, the price for carbon emissions is not set directly, but by the market in a cap-and-trade system. The FuelEU directive is likely to take this some steps further, possibly allowing across- and between-fleet emission caps, thus opening up for strategic collaboration and alliances to be considered as part of the fleet renewal and retrofit process. As a consequence, making informed decisions today that are dependent on, say, the cost and availability of a certain fuel in 2030 or 2040, becomes difficult.

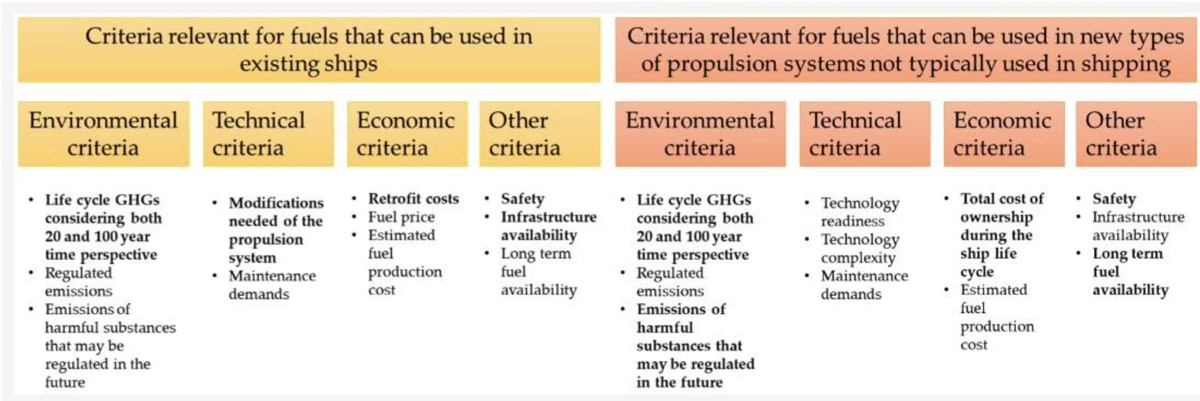


Figure 19: Criteria relevant for forecasting fuel cost and availability (Lagouvardou et al, 2023)

Developing design solutions for lifecycle value delivery

In the two previous sections, we have pointed to the changing needs and requirements along the lifecycle timeline of the vessel, as well as the uncertainty and variability of the external operating context. This leads to the question: How can we, as ship designers, find system solutions that are capable of providing sustained value along this timeline?

First, lifecycle-oriented system performance indicators, such as changeability, flexibility, adaptability and robustness, should be integrated into the design process. However, it is often difficult to make the connection between these high-level concepts and the main design decision variables. One interesting contribution is the efforts by Maggiancalda (2019) towards developing a Life Cycle Performance Assessment (LCPA) tool for the assessment of both the economic and environmental performance of a vessel over its life cycle. More specifically, an effort to quantify the changeability performance of a vessel is developed by Rehn et al. (2018), by making it possible to compare alternative design solutions towards their ability to deliver the required performance over a range of possible future operating scenarios. The changeability concept is closely tied to flexibility and retrofitability, which are both lifecycle-oriented performance concepts that takes into account the value for the shipowner of being able to have cost-efficient options that can be exercised after the outcome of a particular uncertain operating aspect has been revealed, (Lagemann 2023), as illustrated in Figure 20. The basis for the quantification of this value is based on real options models.

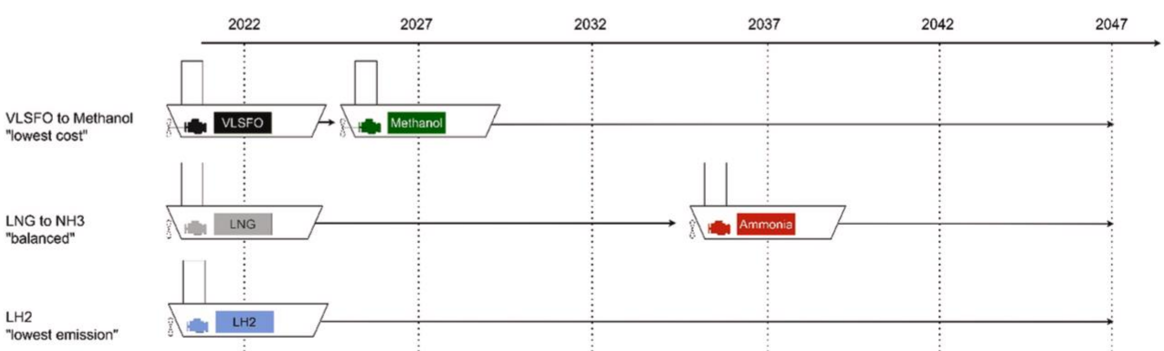


Figure 20: Pareto-optimal lifecycle machinery-fuel configuration with carbon pricing uncertainty (Lagemann et al., 2023)

Lifecycle stewardship consideration at the design stage

Lifecycle aspects of ship design also include those measures taken at the design stage for the continued management of the ship beyond delivery. For ship designers and shipbuilders this also represents a business opportunity. Traditionally, their responsibility for the delivered vessel was capped by the guarantee period. So was also the income stream. Recent developments in digitalization and the Internet of Things (IoT), having fostered a wide array of different digital twin solutions, have provided a platform for ship designers, equipment manufacturers and shipbuilders to maintain a tighter relationship with the customer throughout the lifecycle. Basically, the idea is to provide value-adding services based on both an intimate knowledge of the ship itself combined with real-time data streams from onboard sensors. One example of such services might be the tracking vessel "inventory" all the way to scrapping, proactively offering docking services for repairs, upgrades and retrofits. Another example is online shore-based operations centers which can offer both deep expertise and economy-of-scale by the concurrent management of multiple vessels. Both these examples would benefit from action taken already at the design stage, in which both the digital twin of the vessel is born, and the control and sensor architecture of the vessel is determined. In addition, these operation stage, value-adding services should themselves be designed, preferably according to the same design methodology as the ship itself, (Erikstad 2019).

To summarize, this section has focused on the lifecycle perspectives on ship design. With our common goal of zero emission shipping by 2050, this "cradle to grave" holistic approach, where we explicitly face the uncertainty inherent in the 25-30 years lifetime of the vessel has become even more important.

DIGITAL TWINS IN THE DESIGN AND RETROFIT OF SHIPS

This section provides a review of digital twins (DTs) in the *design* and *retrofit* of ships. It also covers lessons learned from other industries, a proposal for digital twin modelling, and concludes with areas for future research and application of DTs.

Background on Digital Twins for Ship Design and Retrofit

The concept of the digital twin has existed since the beginning of space explorations when NASA implemented similar concepts to a digital twin in the 1960's (Ibrion et al, 2019). However, DTs really became a widespread concept after Grieves (2014) developed a framework of the DT where the information of the physical entity and the virtual entity are synchronized. The DT is envisioned to assist in all phases of the lifecycle but up until now research has primarily focused on the *manufacturing* and *operation* phase and has been specifically lacking in the *design* and *retire* phase. When analysing a ship's life-cycle, Mauro and Kana (2023) suggest incorporating retrofitting into the decommissioning phase of a ship. Therefore this section aims to explore this research gap and determine the state-of-the-art and current limitations related to DT-enabled ship *design* and *retrofit*.

Before proceeding, an overview of DTs is presented. Grieves (2014) provides a clear definition of a DT that is composed of three main parts:

1. a physical product in the real environment composed of information about itself
2. a virtual product in a virtual environment representing the physical product
3. a data connection between these two product actively flowing in both ways as so-called mirroring or twinning

The function of this bi-directional data connection is to process the information from the physical product, update the virtual product, assess the current state, predict the future state, and provide further instructions for the physical product, all in an automated way.

Based on this definition, unfortunately, the term "digital twin" has traditionally been used inconsistently throughout literature, with many virtual and computer models often falsely labelled as a DT. Kritzinger et al. (2018) have provided three distinct types of models to support the nomenclature (see Figure 21), which this state-of-the-art report argues should also be adopted throughout ship design DT-related literature:

- A *digital model* (DM) is a virtual representation of the physical product, but with no formal automated exchange of data between the physical and virtual entity. Data exchange could occur but only performed manually. The DM is mostly used for simulation and planning-based operations which does not require automatic data integration.
- A *digital shadow* (DS) is an extended version of a DM including only an automated data flow from the physical product towards the virtual product by which it is actively updated.
- A *digital twin* (DT) is composed of a physical and virtual product including an automated bi-directional data flow between both entities.

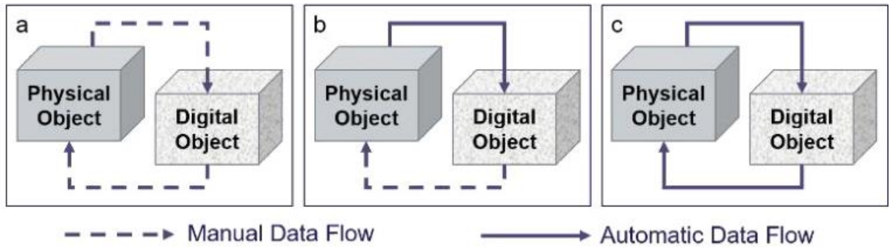


Figure 21: Integration levels between virtual and physical environment for (a) digital models, (b) digital shadows, and (c) digital twins (Kritzinger et al., 2018; Mauro and Kana, 2023)

The bi-directional communication is a crucial element because this enables a mirroring between the virtual and physical entity (Grieves, 2014). This creates opportunities to improve each stage of the ship life cycle through direct monitoring, decision making, and advanced predictive algorithms. Importantly the direct response of the DT creates an opportunity to actively improve ship operation and learn from the responses of the physical entity for future design and manufacturing.

Figure 22 provides a high-level overview of the tasks necessary between the virtual and physical entities to enable a DT:

- *Task 1*: The acquisition of data from the physical to the virtual entity obtained from employed sensors on the physical entity.
- *Task 2*: Perform a virtual test or optimization process in order to improve the performance or decrease the risk of malfunctions or failures of the physical entity.
- *Task 3*: Enacting corrective measures on the physical entity by transmitting data to the actuators of the physical entity using a specified protocol.

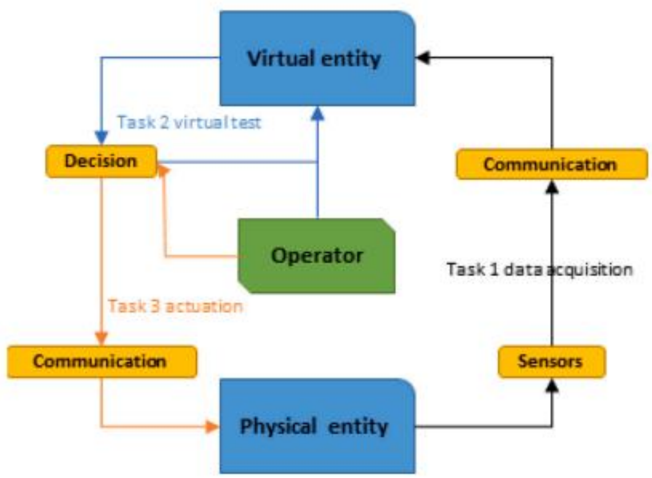


Figure 22: Schematic representation of a DT with the interconnection between virtual and physical entities (Mauro and Kana, 2023)

Sensors could measure characteristics onboard such as the engine room temperature, strain, pressure, electricity consumption or exhaust gas composition which will provide data that can be used to improve the efficiency of the operation of the ship to decrease GHG emissions. Also, environmental sensors can be deployed to measure for example the wind and sea state, outside temperature, sea salinity and GPS to directly respond to environmental changes for optimal operation in changing environments. In order to respond to such environmental and onboard changes task two is crucial to establish a corrective measurement. Lastly, this corrective measurement needs to be translated to the physical entity to alter the operation for improved performance. Such as reducing the speed during increasingly heavy sea state, winds or reducing noise pollution when entering certain (marine) protected areas.

From a ship design perspective, DT based design is not a term commonly used in literature. Especially not in the maritime industry where the concept of DT alone is underrepresented compared to other complex engineering industries (Mauro and Kana, 2023). Even in other industries such as aerospace, civil, and automotive the method for DT-based design is very premature and as a result, is inconsistent and does not have a standardized framework (Psarommatis and May, 2022). There are multiple reasons why it is so challenging to create a detailed DT framework focused on design for new builds. The main challenges provided by previous literature studies suggest three main reasons why:

1. Most importantly the definition of DT has been used inconsistently intertwining the concept of DT with other versions of digital entities.
2. The concept of DT-enabled design with the synchronised DT from Grieves (2014) is relatively new and in a very early stage of development globally.
3. The developments have mainly focused on the operation and maintenance stage and not on design (or retrofit).

This paper proposes an additional reason:

4. When designing a new vessel, the physical entity does not, by definition, exist yet. Thus, properly adhering to the DT definition requiring bi-directional communication between the physical and virtual entity is not possible. Thus, this paper discussed DT-based design to suggest a design process that eventually enables true DT capabilities once the vessel is built.

Mauro and Kana (2023) conclude that there is a large delay in the *design* and *retrofit* phase for DTs, and thus it is necessary to evaluate the state-of-the-art and limitations of DTs in these phases in more detail.

DT-based New Build Design

Currently, most research publications containing conceptual DT applications focus on parts of a ship instead of the total ship itself. A systematic review of the literature finds only two available publications which address a DT theoretical framework considering new-build methods, and of which only one is associated with the design of the whole ship (Xiao et al., 2022). The authors propose a DT framework proposing the use of a vertical-horizontal design method of a new-build regarding the total ship throughout its life-cycle phases. This framework is still under development. Even though it provides promising conclusions, it is still a theoretical framework with in-depth research still being conducted as mentioned by the authors. Nevertheless, no articles are available regarding concrete applications of DTs linked to new-build design methods, only for theoretical and conceptual cases.

The remaining articles concern mostly subsystems of a vessel and relate to conceptional applications or only provide a general description of such an application (Arrichiello & Gualeni, 2020; Nikolopoulos & Boulougouris, 2020; Pérez Fernández, 2021; Stachowski & Kjeilen, 2017). Erikstad (2017) has also identified this trend of subsystem DT application but indicated the potential of getting closer to achieving a DT of a complete ship when such subsystem DTs are merged.

Additionally, very few papers include essential information such as specific methods, input data, output data or reliability of the design. Following the classification by Tao et al (2019) and used by Mauro and Kana (2023) the current literature on DT-based ship design is in a so-called formation stage, meaning, “very few papers are published as the technological foundations are not mature enough to support effective applications”. As a result, it will likely be challenging to iterate and develop these methods further within the maritime community outside of the specific research groups where they were developed, hampering overall progress.

Finally, a distinction can be made between (1) the design of a physical entity while consequently designing a DT specifically tailored to the physical entity and (2) developing a virtual space in which DTs can be developed for different types of ships. A choice needs to be made to establish a development direction. This distinction has been pointed out by Wang et al (2022); however, they do not mention an argument to which development direction is favourable. This state-of-the-art report argues, nevertheless, for the second direction, as it provides the potential for generality and reusability of the virtual space, enabling greater usability potential.

DT-based Retrofit Design

Even though it is not performed for every ship and therefore not considered as a general life-cycle phase, retrofitting is common to perform when aiming to reduce emissions or to improve the onboard systems (RINA, 2020). There are limited available publications linked directly to DT application for ship retrofitting, which can be explained by the fact that the retire or retrofit phase (including multiple retrofits) is the last stage of a ship’s life-cycle and subsequently will also be the last stage to be fully investigated with regard to DTs. In order to fill this gap it is proposed to examine research done on DTs in the operational phase which will provide sufficient information on design decisions linked to retrofitting. With ship data acquired during the operational phase of the vessel and processed by a DT, design decisions for a retrofit can be derived throughout the DT.

Two publications have been identified which present a conceptual framework to integrate DTs with an existing ship (Zhang et al., 2022) and virtual system (Mouzakitis et al., 2023). Zhang et al (2022) propose the construction of a DT for an already existing research vessel, ‘Gunnerus’. Although the project is still ongoing, the article provides a DT architecture including the data-driven design building block method using the Open Simulation Platform, an open-source simulation platform. Even though a unique vessel is being considered, the authors aim is to provide a standardized DT concept for the maritime industry.

Additionally, Mouzakitis et al. (2023) address the importance of using high-performance computing together with big data analytics to develop, and therefore contribute to high-level digital products for the maritime industry. The DT architecture includes a proposed data integration into the existing unified system within the 'VesselAI' project. Additionally, the Digital Twin for Green Shipping (DT4GS, 2024) project aims to develop DTs for existing commercial vessels, with applications in container ships, bulk carriers, tankers, and RO-PAX ferries. This project is still ongoing.

With maritime DT applications still being relatively new, it is logical to assume publications regarding retrofitting will become available in the future. This paper argues for additional research on DTs in the operational phase to support information regarding a possible retrofit, given the fact retrofitting is being performed to extend the life-time (e.g., operational phase) of a ship.

For both new-build and retrofit designs a clear research gap is identified regarding the application of DTs. When examining the current state-of-the-art of DTs for ship design and retrofit, the literature showed that scientific research into maritime DT applications is still in the early stages of development but is rapidly growing. Regarding new-builds, publications only cover conceptual DTs or consider a subsystem of the ship, not the total ship. Furthermore, limited available publications were found regarding DTs for retrofit design. A research gap is identified for DT application of new-build design considering the total ship and retrofitting in general.

Lessons Learned from Other Industries

In other industries, there are DT-based design challenges that have been researched but have not been addressed yet in the ship design industry. A large amount of literature referencing DT-based design is not specifically aimed at a certain industry. As a result, the proposed design methods are not very detailed. However, some important frameworks have been developed which could influence ship design as well. For example one of the ship design challenges stated by Fonseca and Gaspar (2020) is the complexity of determining the business value of the DT. Newrzella et al (2022) propose a method to define a selection of use cases and data sources to start a pilot phase, derived from the market needs and the most impactful data sources. Since the shipping industry is relatively sensitive to market needs and business value, an approach to determine what DT use cases to develop from the early design stage is fundamental.

Additionally, in the literature review by Psarommatis and May (2022) it is concluded that the manufacturing industry, which is furthest ahead of other industries, also encounters the same problem as the ship design industry specifically related to the research gap exploring DT-based design methods. The majority of DT-based design papers either develop technologies for only one-time occurrences or are not stated. The definition of the communication within the DT has been categorized as unstated or manual, with manual being the most common, which is in contradiction to the formal definition of DTs proposed by Grieves (2014). The large majority of the papers do not verify their methods nor include input and output parameters. As a result, most methods are only suitable for one-time use and cannot be further developed. Thus, it appears that the manufacturing industry has similar challenges to ship design. Psarommatis and May (2022) propose a flowchart of the design decisions needed before the DT can be developed (Figure 23). This targets shortcomings in the current literature that the maritime industry also encounters. These steps are general and can be integrated into the ship design process with minor modifications, depending on the intended application.

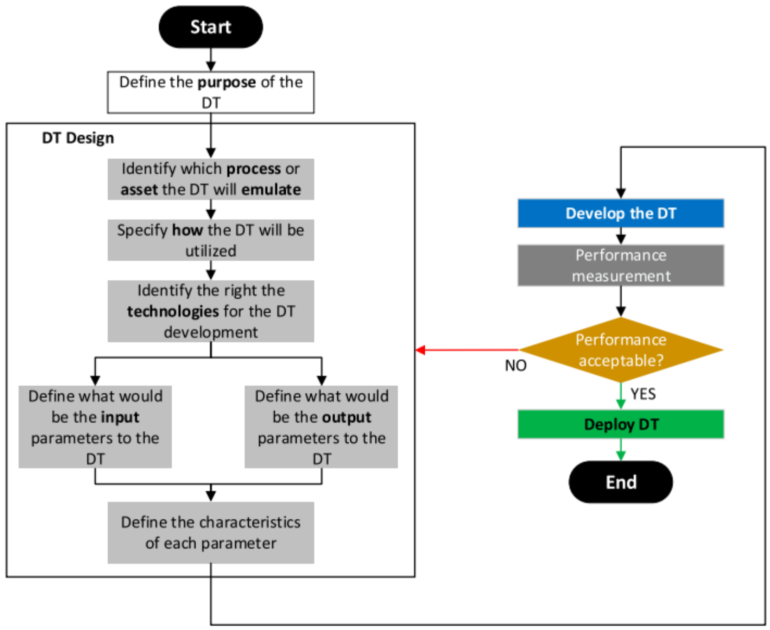


Figure 23: Proposed DT-based design method by Psarommatis and May (2022)

Finally, the aerospace industry has more experience in the application of DTs and proven effectiveness in quality improvement. NASA is working on the integration of model-based systems engineering (MBSE) and DT design (Weiland, 2021) which has also been explored in the shipping industry (NAVAIS, 2022). MBSE enables the inclusion of contributors and stakeholders, facilitating collaboration throughout the product life cycle, and resulting in more efficient data exchange and shared model information compared to traditional methods (Lopez and Akundi (2022). MBSE can also handle fast changes, and improve the collaboration of engineers and digital machines by providing knowledge-sharing infrastructure, automating designs, and simulating system behaviour (Weiland, 2021). This paper thus argues for additional research effort within the ship design community in the application of formal MBSE to support DT-based design and retrofit as it provides a promising framework to develop a virtual space in which digital twins can be developed for different types of ships.

Digital Twin Modelling for Ship Design and Retrofit

This section provides a high-level DT modelling process that can support DT-based design. It is designed to be generic and thus also be coherent with the application of MBSE stated above. Before starting the process, the objective of a DT must be determined which covers the composition and modelling process of the DT. The DT objective will indicate which virtual models are required for the DT. The DT output is based on performing simulations, using available operational data. The composition of the virtual part of the DT depends on this data, as this will determine the feasibility of modelling certain parts within the DT, and thus drives the modelling process (Giering & Dyck, 2021). By investigating the available data, the virtual models which are feasible to construct are identified. Finally, the overlap between the required models (derived from the DT objective) and the feasible models (derived from the available data) provides the models to be selected for the final DT (see Figure 24).

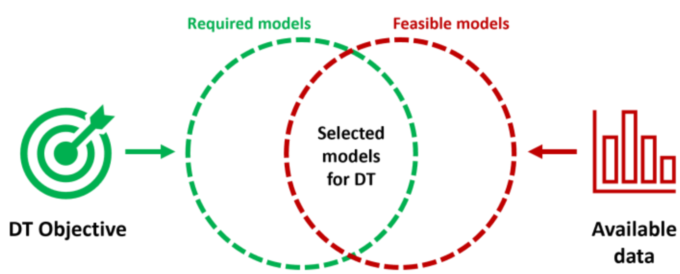


Figure 24: Selection process for DT models (Hermans, 2024)

After establishing the DT's objective and the model selection process, the modelling phase involves the following general steps:

1. **Set-up the data acquisition**: To acquire the data for the DT, a data acquisition system needs to be established, which collects the information required to model the DT, and functions as a collector for the bi-directional data connection.
2. **Establish a data pre-processing framework:** The data needs to be pre-processed in order to be of use as input for the virtual models. García et al (2016) discuss key data preprocessing techniques in the field of computer science, which can also be leveraged for DT modelling, such as data cleaning and normalization. A preprocessing framework depends on the chosen modelling approach, and consequently on the type of data. By establishing an effective framework, redundancies are reduced regarding connected features within the DT (Autiosalo et al., 2019).
3. **Choose modelling approaches for virtual models:** The three different modelling approaches adopted in standard data-science literature are: black-box, white-box, and grey-box. Black-box models are digital models purely based on statistical techniques in order to find relationships between a set of empirical input data and a set of desired output data. White-box models are the exact opposite, and are constructed based on physical principles, theoretically derived set of equations and experimental-derived data. A grey-box model aims to achieve the advantages of both model types by combining the analytically and experimental-driven methods of a white-box model to achieve physical accuracy, and the statistical techniques of a black-box model to identify patterns (Ehmer & Khan, 2012).
4. **Perform model training in case of statistical-based models:** Through training, the model is calibrated in order to achieve the acceptable accuracy. Model training is required for black-box models.
5. **Verify and validate (V&V) the virtual models:** When the chosen models are constructed, and trained in case of applying a black-box or grey-box approach, they need to be verified and validated to ensure the accuracy and reliability of the chosen modelling approaches
6. **Integrate the virtual part with the physical part:** After the models have been verified and validated, they can be integrated into the DT infrastructure. Following the DT definition by Grieves (2014), the output of the virtual models needs to be connected in an automated way to the physical ship. As it is related to the physical vessel, this output can directly be received and used by the respective vessel. In the case of a DT for retrofit purposes, the output will relate to recommendations regarding design decisions. It is considered that the output of the models will drive the retrofit design, and after the retrofit has successfully been performed, the virtual models will represent the modified vessel. Thus, after the retrofitting occurs, the virtual-physical integration can take place. With the integration completed, the DT is established and can be used for operational purposes, such as performance monitoring.

Figure 25 shows a schematic representation of the transition towards a DT for retrofitting. The integration step is performed at the end and can occur simultaneously with the completion of the retrofit (step 5). The final retrofit DT originates from a digital model which represents the ship (step 1), and which is further investigated for possible retrofit options (step 2). The chosen retrofit design (step 3) will then be used for the actual retrofitting of the respective vessel (step 4).

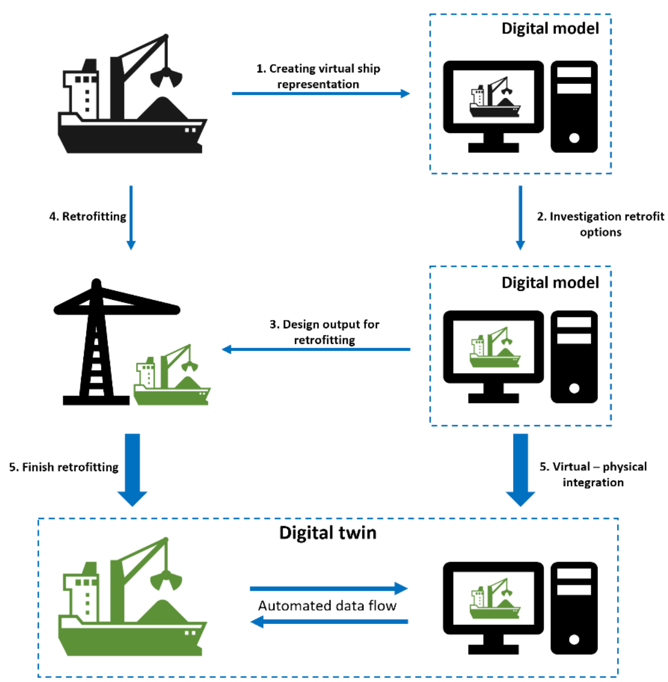


Figure 25: The development of the digital twin for retrofitting (Hermans, 2024)

ARTIFICIAL INTELLIGENCE

Erikstad and Lagemann (2022) have already addressed the introduction of artificial intelligence (AI) in ship design in their IMDC 2022 State-of-the-Art report. However, it was a few months later that the world was astonished by the release of OpenAI's Chat Generative Pre-trained Transformer (ChatGPT) at the end of November 2022 (Wikipedia, 2024). Since then, the research on the potential benefits, limitations and challenges of the application of AI in the ship design field has intensified.

According to the definition adopted by the European Commission in 2018 (Boucher, 2020) "*AI refers to systems that display intelligent behaviour by analysing their environment and taking action – with some degree of autonomy – to achieve specific goals*". There are many attempts to classify the key technologies that are associated with AI. According to Boucher (2020) for EC there are three main stages of development. The first was the symbolic AI (or Rule-Based AI) that included expert systems, Artificial Neural Networks (ANN), deep learning and fuzzy logic. The second stage includes the introduction of machine learning (ML) algorithms such as surrogate models and data-driven intelligence. The third wave includes 'strong' or 'general' AI (AGI) that shows intelligence in a wide range of problem spaces. This includes Natural Language Processing (NLP) algorithms and in the future artificial superintelligence (ASI).

Huang et al. (2022) have attempted a review of the research addressing ML's application in sustainable ship design and operation. Their classification of ML models was inspired by Sarker (2021).

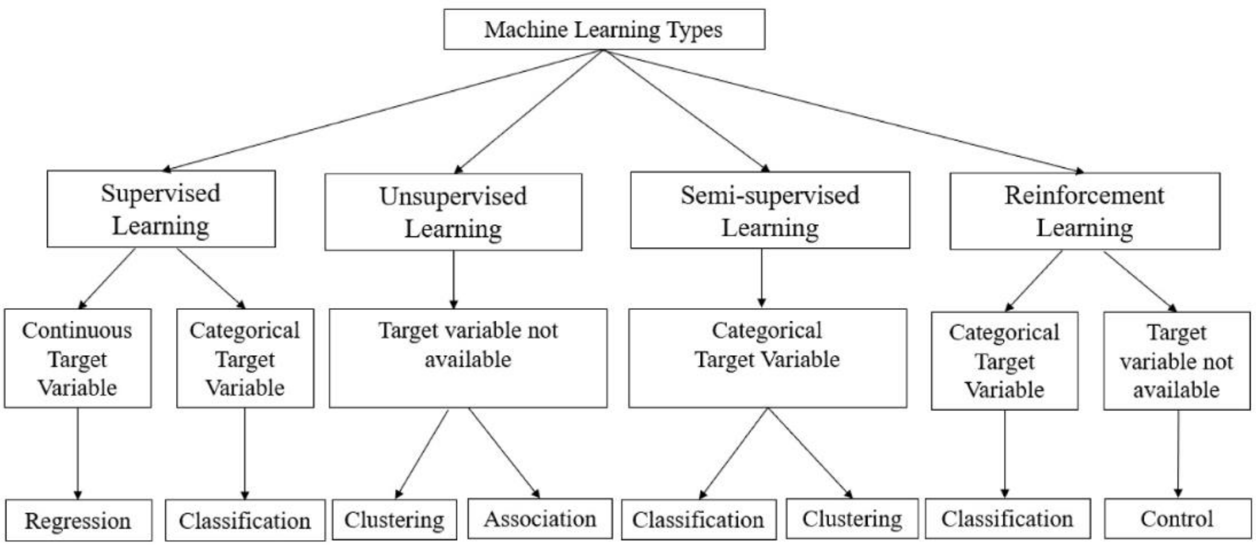


Figure 26: Classification of Machine Learning according to Huang et al. (2022) inspired by Sarker (2021)

AI accelerating applications in ship design provide solutions to several challenging problems. These include hull optimisation, performance prediction, holistic design optimisation; accelerated structural analysis and material selection; energy efficiency, decarbonisation and environmental impact; safety analysis and compliance with the applicable rules and regulations; and prognostics and diagnostics for predictive maintenance.

Hullform optimisation

Yu and Wang (2018) introduced a Principal Component Analysis (PCA) methodology to compress the geometric representation of a group of existing vessels. The resulting principal scores are used to generate many derived hull forms, which are evaluated computationally for their calm-water performances. A Simple-Source Panel Method (SPM) based on potential flow theory was used to calculate the wave resistance, accelerated by a Graphic Processing Unit (GPU). The results were used to train a Deep Neural Network (DNN) establishing the performances of the different hull forms. Based on the DNN's evaluation, a large-scale search for optimal hull forms is performed very quickly and with increased flexibility. However, the authors note that the pool of parent hulls should be expanded and CFD and EFD results should be included in the training to increase the accuracy of the DNN predictions. Additional performances should be evaluated to establish a more comprehensive optimization process.

Panchal et al. (2019) in their guest editorial for the special issue on ML for Engineering Design, argue that machine learning algorithms have an evolutionary impact on mechanical design, uncovering hidden patterns in data and developing autonomous systems. DNN and other modern ML techniques are enabling progress in AI. Examples include ANN, Gaussian processes, clustering techniques, and Natural Language Processing. They also point out that engineering design research has more recently benefited from the introduction of deep learning techniques such as convolutional neural networks (CNNs) and generative adversarial networks (GANs). The research they present in the special issue introduces a first taxonomy of the area: (i) ML techniques to support surrogate modelling, design exploration, and optimization, (ii) ML-supported design synthesis, (iii) extraction of human preferences and design strategies utilizing ML, and (iv) ML-informed comparative studies and research platforms from design researchers support. The editorial team recognizes that ML has already applications in modelling human decision-making, market system design, human or surrounding environment interactions with products , design for reliability, informing the design using of real-time data from products (design-for-X),where a particular aspect of the lifecycle or across several aspects of the lifecycle are benefit for the analysis of data gathered. Security, privacy, cyber-resilience, trustworthiness and other non-traditional design challenges in engineering design, arising from smart products and systems, present emerging opportunities for the use of ML.

Grigoropoulos et al. (2021) presented a mixed-fidelity method to optimise hullforms combining genetic algorithms (GA), hydrodynamics potential flow numerical codes and a surrogate model based on ANN to account for the viscous effects. The ML tool is trained to capture the impact of viscosity on the flow around the stern of the vessel by analysing the results of a series of Design-of-Experiment (DoE) runs with a Reynolds-Average Navier-Stokes (RANS) solver. The approach accelerates the evaluation of the calm water resistance of the various designs and reduces the computational time required to reach an optimal hull design. The final design was evaluated with the RANS solver and the accuracy was satisfactory. The authors note that the exact number of neurons in the network are less important than the quality and quantity of the input data used for training the ANN. However, they recon that full-scale simulations at large Reynolds numbers are still challenging.

Ao et al. (2022) presented a data-driven multiple-input neural network (MINN) model to predict the total resistance of the ship's hull with the objective of avoiding inconsistencies from input parameters. It utilised three Fully Connected Neural Networks (FCNNs). The authors argue that the developed AI-based ML algorithm can assist the ship hull design process in real time by accurately providing the total resistance. They validated their results against a potential flow resistance prediction method. Through their validation studies, the authors have shown that a well-trained ANN can accurately estimate the hydrodynamic performances of a hull based on its geometry modification parameters. Therefore, the authors claim that the approach gives an accurate and fast AI-based method that provides optimum estimation accuracy in the entire design space.

Bagazinski and Ahmed (2023a) proposed a generative AI model based on a guided diffusion algorithm for parametric ship hull generation. They used a denoising diffusion probabilistic model (DDPM) that created the tabular design vectors of a ship hull. The model managed to improve performance through guidance. It utilised the dataset of 30,000 parametrised hull forms called Ship-D (Bagazinski and Ahmed, 2023b). Utilising 45 hull parameters and 49 algebraic feasibility constraints and guidance from performance prediction models, the algorithm was able to generate high-performance designs with only information learned from the low-performing hulls in the dataset. However, the significant reductions in wave drag were calculated using Michell's integral and they were not confirmed by more precise tools (e.g. VOF CFD) and the impact of other design changes (e.g. increased displacement) was not compensated by changes to other design parameters such as lightship, deadweight, stability etc.

Khan et al. (2023) introduced the generic parametric modeller ShipHullGAN. Deep convolutional generative adversarial networks (GANs) were used for an adaptive representation and generation of ship hulls. The model is trained on a dataset of more than fifty-two thousand physically validated designs. They included a variety of different ship types, such as bulkcarriers, tankers, container ships, crew supply vessels and tugboats. All training designs are converted into a common geometric representation using a shape extraction and representation strategy. They have the same resolution, as typically GANs can only accept vectors of fixed dimension as input. Right after the generator component, a space-filling layer was placed. Its purpose was to confirm that the trained generator could cover all design classes. The designs are provided in the form of a shape-signature tensor (SST) during training. It harnesses the compact geometric representation using geometric moments that further enable the cost-effective integration of physics-informed components in ship design. The authors argue that comparative studies and optimisation cases have shown that ShipHullGAN was capable of producing designs a broad spectrum of designs, both traditional and innovative, with geometrically sound and practically viable configurations.

Sharma et al. (2023) review Physics-informed Machine Learning (PIML) and how it integrates ML with domain knowledge. The authors suggest that higher data efficiency and more stable predictions can be achieved. Therefore, high-fidelity numerical simulations of complex turbulent flows can be augmented or even replaced. The authors categorise ML into unsupervised, supervised, and semi-supervised. Unsupervised learning refers to algorithms that learn from unlabelled data, This is opposed to supervised learning where algorithms recognise patterns of input–output relationships from labelled data. In semi-supervised learning, algorithms contain characteristics of both unsupervised and supervised learning. Regression and classification problems are typical applications of supervised learning. The PIMLs are the most recent step in the evolution of ML towards their applicability in fluid mechanics problems as they combine ML techniques with physics knowledge, and model loss

functions as can be seen in Figure **27: Methods for incorporating knowledge from physics into supervised learning framework models**
(Sharma et al., 2023)

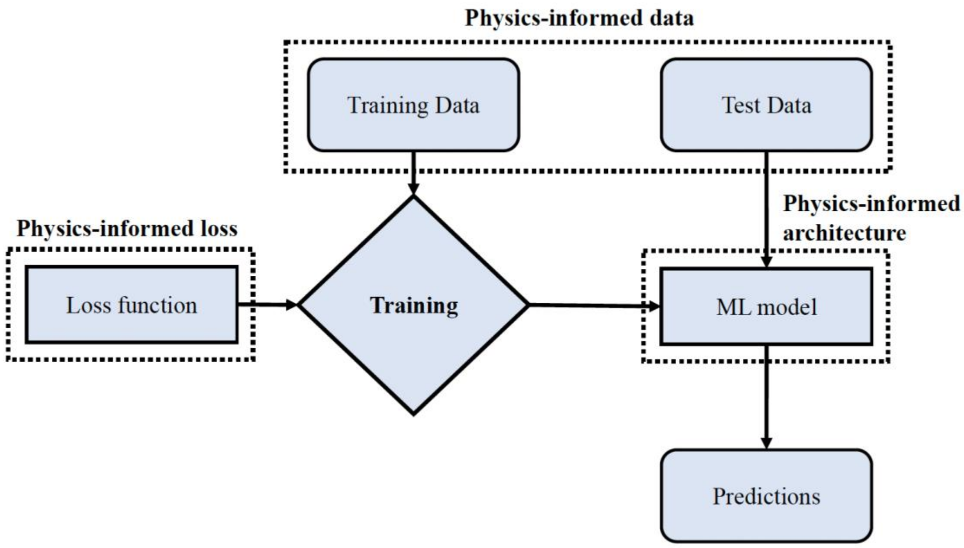


Figure 27: Methods for incorporating knowledge from physics into supervised learning framework models (Sharma et al., 2023)

Majnarić et al. (2024) investigated the use of ML-based determination of a containership's main particulars at the early design stage. They applied a synthetic data generation technique for generating a large amount of synthetic data points regarding container ships' main particulars, utilising a multilayer perceptron (MLP) regressor on both original and synthetic data mixed with original data points. The models were validated based on real data showing very good agreement.

Performance Prediction

Wang et al. (2022) present a deep neural network (DNN)-based approach to convert hull designs to condensed representations, generate innovative designs, and based on their hydrodynamic performance, optimize the synthetic design. The DNN-based 3D ship hull encoding and optimisation framework is shown in Figure 28**:** 8. It consists of three components integrated with CFD simulations: ship data augmentation and parameterization, VAE, and design optimization with virtual screening.

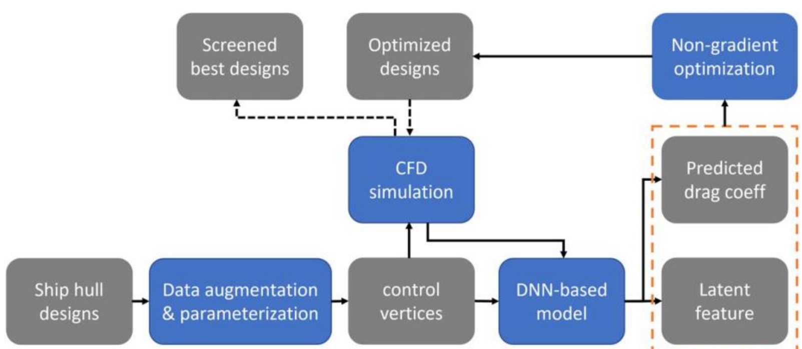


Figure 28: Overview of the data-driven ship 3D hull encoding and optimization framework (Wang et al., 2022)

A variational autoencoder (VAE) equipped with a hydro-predictor has been developed to reconstruct the geometry of hulls by reconstructing the Laplacian parameterized hulls. It also encodes the CFD-simulated resistance. Perlin noise mapping and free-form deformation (FFD) data augmentation algorithms generate the training set from a parent hull. This VAE model is then used to search efficiently through a vast array of generated hulls to identify those with minimum resistance. The most promising hulls are verified using CFD calculations. Numerical experiments verify the ability of the framework to reconstruct the input geometries and predict their resistance accurately using a convolutional neural network (CNN). The authors note that it has produced new hull designs showcasing a 35% resistance reduction compared to the parent design. However, despite its adeptness, it is limited to intraclass ship design as the VAE reconstruction network is highly model-specific.

Hodges et al. (2022) utilized Siemens' NX CAD software to parametrize the hull form of MV Regal with 12 independent geometrical variables. They determined the powering requirements of the designs using the CFD solver Simcenter STAR-CCM+. Then, utilizing the results, they created in Simcenter ROM Builder and Monolith surrogate models. The workflow of the methodology is shown in Figure 29. The outputs of the models include torque, total resistance, powering, and propulsion metrics. These were then supplemented with additional ML CFD predictions for local field results including the wake fraction at the propeller, the generated wake, and the shear and pressure loads on the hull. The authors depict the capabilities of ML models to predict accurately the local field (see Figure 30), and their potential of enhancing the hull optimization pipeline.

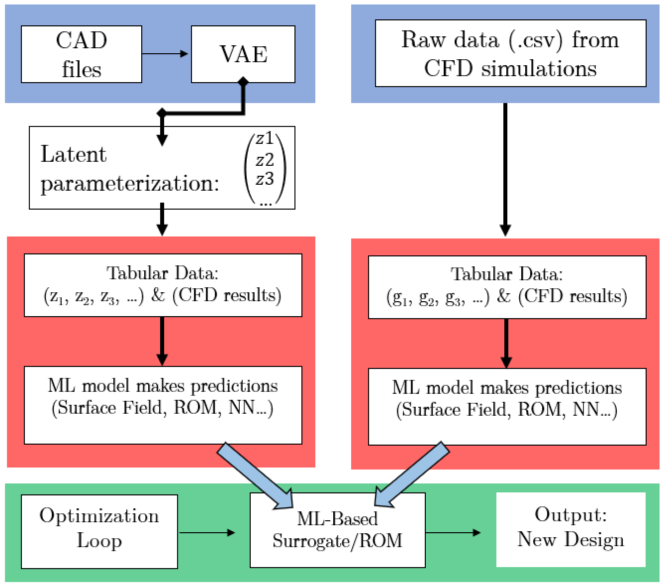


Figure 29: The different workflows used by Hodges et al. (2022)

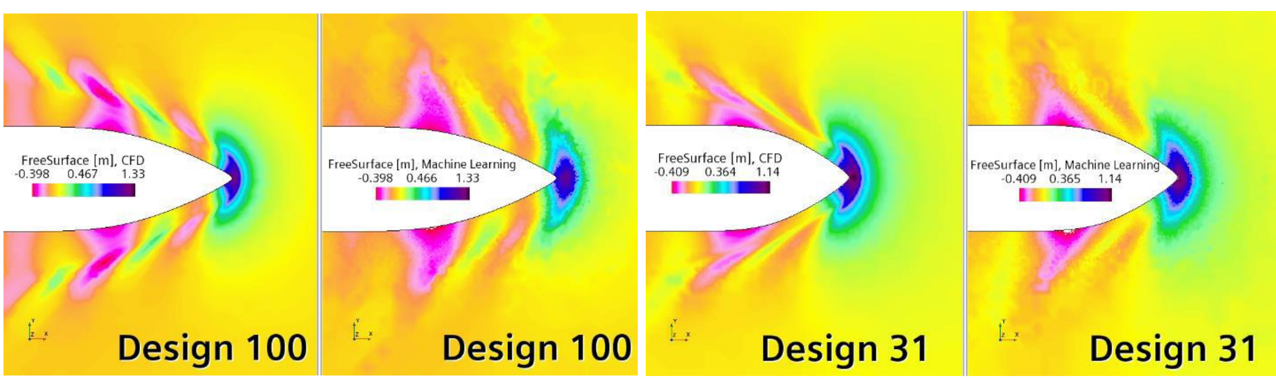


Figure 30: Free surface elevation comparisons between CFD simulation and ML model predictions (Hodges et al., 2022)

Safety Analysis

Louvros et.al. (2023) described a novel approach that introduces a fast decision support tool which can provide information regarding the ongoing damage stability casualty utilizing prior knowledge gained from simulations. Case-based reasoning and Machine Learning methods are used, providing real-time predictions based on "analyzing" a dataset of pre-run damage scenarios. In this way, the lengthy and costly computations that describe the actual flooding phenomena can be bypassed. Case studies simulating realistic scenarios are presented to showcase the performance and practical application of the methodology.

Holistic Design Optimisation

Nazemian et al. (2024) presented a Machine Learning (ML) tool for calm water resistance prediction and used it to develop a systematic series for battery-driven catamaran hullforms. Furthermore, they employed the ML predictor for design optimization using a GA. For the dataset training, three regression models were tested, namely, Regression Trees (RTs); Support Vector Machines (SVMs); and Artificial Neural Network (ANN). The authors use the framework for the optimization of several catamarans, including dimensional and hull coefficient parameters based on resistance, structural weight reduction, and battery performance improvement. Lackenby transformation is initially used to explore the design space, and then, a novel self-blending method generates new hullforms based on two-parent blending. Finally, the generated data of the case study are encoded in an ML model. The ANN algorithm has shown a good correlation with the expected resistance. Accordingly, by choosing any new design based on owner requirements, GA optimization obtained the final optimum design by using an ML fast resistance calculator. The design of a 40 m passenger catamaran vessel was optimised in a showcased study. The framework achieved a 9.5% improvement proving that combining ML and GA optimization may accelerate significantly the ship design process.

Energy efficiency, decarbonisation and environmental impact

Nikolopoulos and Boulougouris (2023) presented a Robust Holistic Ship Design Approach (RHODA) using voyage simulation and surrogate models. The authors deployed the framework for the optimization of Zero-Emission Ships. They implemented the simulation-driven optimization in the case study of an NH3-fulled Large Bulk Carrier. The framework was adapted to cover the ship and fuel-specific aspects of the design of the Zero-Emission ship configuration

Zhang et al. (2024) utilize a deep learning method for the prediction of ship fuel consumption. Their approach makes use of big data from sensors, voyage reporting and hydrometeorological data, summing up to a total of 266 variables. Their model is trained based on results from sea trials of a Kamsarmax bulk carrier. Using a Decision Tree (DT), patterns are recognized within the available dataset. Implementing a deep learning model, the influence of variables such as sailing speed, heading, displacement/draft, trim, weather, sea conditions, etc. on ship fuel consumption (SFC) is established. This is achieved by incorporating a DLM based on Bi-LSTM with an attention mechanism. The methodology is validated using k-fold cross-validation and implemented in a case study. The author concluded that the method could be useful in the context of a decision-support system for environmentally friendly operations, subject to further testing and validation.

Other areas

Mikulić and Parunov (2019) presented an overview of the AI and ML state-of-the-art in different areas of the maritime industry. This included design, structures, hydrodynamics, forecast of environmental factors, corrosion, production, and machinery. The authors concluded with recommendations for potential implementations.

AI and ML algorithms have also found their way into the integration of ship design and ship production in the form of the recently started Horizon Europe Project ESY (2024), where digital tools will support sustainable shipbuilding practices.

CONCLUSIONS AND WAY AHEAD

Conclusions

In today's era of smart digitalization in the frame of Industry 4.0, recently introduced digital/software tools and systems have increased the efficiency and quality of the life-cycle ship design process. Parametric optimisation and simulation-driven design, product lifecycle management, digital twins and artificial intelligence are nowadays frequently used by the maritime industry during the commissioning/quality control activities and in the various phases of ship design, ship operation and ship production.

Classical and novel concepts of ship design and the assessment of life-cycle operation are nowadays implemented in versatile, integrated design platforms, offering the user a vast variety of options for the efficient development of alternative ship designs by use of tools for their analysis and parametric, multi-objective optimisation with respect to all relevant (ship) design disciplines, as well as virtual prototyping. Some design software systems (e.g., as developed in HOLISHIP) adopt an open architecture that allows for the continuous adaptation to current and emerging design and simulation needs, flexibly setting up dedicated synthesis models for different application cases. The exploration of the huge design space is enabled by the use of automated parametric models of significant depth, which are processed with reduced lead time.

Simulation-driven ship design has become an important part of today's design teams and the authors believe that it will play an even more decisive role in the future. As presented in sections *Parametric Ship Design Optimization*, *Simulation-driven*

Ship Design and *Artificial Intelligence* the trend is to address more complex design tasks while doing so with higher efficacy. SDD campaigns increasingly accommodate more objectives and several disciplines. This is because competition continues to be high, calling for better products, while the need for sustainable shipping has become evident as is now also reflected in recent legislation. Furthermore, the environment in which design teams need to make decisions has become more complicated over the last years. Potential solutions for energy-efficient shipping are developing more rapidly – with some that are just emerging – while the prediction of available fuels, trade patterns and retrofits for ships in service is presently rather difficult, adding uncertainty and calling for flexibility as elaborated in section *Ship Production and Lifecycle Management*.

We believe lifecycle aspects of marine systems design will become even more important in the coming years. Our common ambitious goals for net zero 2050 will be the main driver. Business-as-usual is not an option. Nor are currently available technology, energy carriers, concepts of operations and regulatory framework sufficient to solve this problem. Thus, innovative and even radical measures are needed – but what this will turn out to be is not yet known. For the maritime industry, this is a severe risk for most, but also an opportunity for those who are able to make and implement the best lifecycle strategies for business development, fleet renewal, retrofits, and operations. For the marine systems design community, it poses a challenge for the years ahead to develop the necessary models, methods and tools to foster change built on a holistic, lifecycle perspective.

A review of the state-of-the-art of digital twins in the design and retrofit of ships concludes that there is currently no standardized design method or approach for DT-based design or retrofit within the ship design industry, or even in other relevant industries. Thus, this state-of-the-art report argues for four points. First, ship design literature should be consistent with their terminology when researching and applying DTs. This paper argues for the DT definitions proposed by Grieves (2014), and Kritzinger et al. (2018). Second, the development of a standardized DT-enabled framework, applicable to both new-builds and retrofits, which is flexible, reusable, and verifiable, and includes, among others, specific methods, input data, output data and reliability of the design would help with the research and innovation in this domain. This should be done to support the development of a virtual space in which DTs can be developed for different types of ships. Third, additional research and application focus should be placed on the use of formal MBSE to support DT-based ship design and retrofits. Finally, additional research focus should be placed on DTs in the operational phase specifically to support retrofitting to extend the lifetime of a ship, increase its energy-efficiency and improve its operation.

The integration of AI in ship design is set to accelerate, expanding from the conceptual phase where its benefits are already evident. AI's role is expected to grow across all stages of design, including hull optimization, performance prediction, and structural and safety analysis. Despite these advancements, engineers face challenges such as ensuring the transparency and verification of AI-generated results, as AI learning is ongoing. Additionally, the impact on the training and employability of future engineers is a concern. The adoption of these tools could significantly reduce task completion times, but there is scepticism about their potential negative effects on job availability in the sector. Naval architects and marine engineers must adapt to leverage AI's advantages while mitigating its challenges.

Way Ahead

The complexity of solving multi-objective and even multi-disciplinary design tasks is intrinsically high since many free variables are involved and many high-fidelity simulations are needed. Surrogates and ML have been proposed to cope with high complexity and to more easily capture mutual influences. In order to provide the necessary training data Design-of-Experiments are utilized. There currently are several approaches to reduce the number of variants that need to be run along with the computational effort that has to be spent: (i) The reduction of the number of free variables by dimensionality reduction, see for instance Diez et al (2015), (ii) the mixture of simulations of different fidelity, see for instance Pellegrini et al (2022), and (iii) the adaptive sampling of design spaces, see for instance Serani et al (2019).

The abundance of data produced during SDD campaigns should and could be utilized more intelligently and more systematically in the future, see section Digital Twins in the Design and Retrofit of Ships. The various levels of digital representation (i.e., model, shadow and twin) can certainly benefit from design data and vice versa. Here, one challenge lies in ship hydrodynamics where full-scale simulations by means of CFD are very resource-intensive and, unfortunately, are difficult to verify by means of reliable measurements while sailing in accurately known weather conditions. Here, the industry at large appears to be still at the beginning of developments.

There are naturally several trends that have not been discussed in this paper so as to deliberately limit its scope. Yet, some of them should be briefly mentioned as they may influence the not-too-distant future in ship design: (i) Cloud solutions, even though still looked at with a certain skepticism when it comes to sensitive data, (i) web-based applications and micro-services that could help increase access to more design teams and “democratize” the usage of high-fidelity simulations at acceptable costs while ensuring results of high quality.

Last, but not least: the complexity of the employed design methods, software tools and design platforms has created an increased demand for proper training of users of software platforms in information technology and beyond traditional naval architecture. This calls for an urgent adaptation of the curricula of university education in naval architecture and marine technology. Ship design is a synthetic, multi-disciplinary field and only properly trained naval architects will be able to assess the validity of results of simulation tools/design software platforms and take proper decisions on the way ahead in stages of the ship design process.

CONTRIBUTION STATEMENT

Author 1: Conceptualization; supervision; writing introduction and chapter on parametric ship design optimisation; paper consolidation; review and editing. **Author 2:** conceptualization; writing chapter on Artificial Intelligence – review and editing. **Author 3**: conceptualization; writing chapter on Life Cycle Management– review and editing. **Author 4:** conceptualization; writing chapter on Simulation-driven Ship Design – review and editing. **Author 5**: conceptualization; writing chapter on Digital Twins - review and editing.

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