AI Generated Design for a Greener Maritime Sector

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The Maritime Sector, involved with shipping goods, people and services by sea, and carry out work operations as sea, is under pressure to conduct a shift towards greener operation, and more efficient energy use. One of the approaches is to couple vessel- and environment data together with other operational data in the form of a digital twin, to better calculate the most efficient way to operate under which conditions. A central challenge to this approach is to understand how to present the data to support decision making for actors in the maritime sector, such as ship crews, who are already working in a complex, data rich environment subject to regulations and operational requirements. This design case considers how AI-generated tools can be used to support an exploratory approach to designing decision making tools for the maritime sector in support of the green transition.

Additional Key Words and Phrases: Interaction Design, Machine Learning, Digital Twin, Green Shipping

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1 Introduction

Maritime Digital Twins (MDT) aims to make use of Digital Twin (DT) data from ships to optimise energy use and reduce carbon emissions resulting from maritime transport. A Maritime Digital Twin covering the life cycle of ships from the Norwegian shipping company DOF AS has been designed by the non-profit organisation Terravera AS, and the authors of this paper together with DOF and Terravera are currently exploring how to put data from the MDT into operational use by actors in the martime sector, such as ship crews, in support of the transition to greener shipping. The research is currently in the planning and proposal stage.

We focus on data from two use cases: engine configuration and hull/propeller optimisation. To make the data usable, MDT uses techniques from predictive machine learning (ML) to analyse and present data in a way that matches with the professional needs of the stakeholders involved. To that end, MDT uses techniques from sustainable Human-Computer Interaction (HCI) and interaction design to create interfaces to support sustainable decisions in maritime operations. This is a challenge because even though environmentally relevant data exist, they need to be made actionable for operators in a professional context that is complex and subject to a multitude of demands and operational risks. With increasing pressure on climate and the environment, it is important to accelerate the reduction of greenhouse gas emissions through incremental steps taken now rather than relying on taking large steps later. We can obtain much needed cuts through maximising the value of already existing data.

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The users in our design case are various operators involved in decision making in the maritime sector, including ship crew and land based planners and decision makers. Sensors placed on the ships, already provide up to 200 data points per ship, providing a data stream that can be analysed for how to optimise shipping operations. Machine learning techniques can be used to better understand how decisions affect the performance of the ships, which in turn can be used to make decisions that are environmentally beneficial. Simultaneously, Large Language Models (LLMs) are being explored as to how they can enrich design processes [15]. We are interested in investigating how LLMs can be used to explore the design space, i.e. the complex environment of shipping operations, and create personas and user stories, that have relevance to, and provide basis for prototyping interfaces to the machine learning outcomes. We are also curious about how generative design can feature in the overall design and development process.

1.1 Design Case

Digital twins are virtual counterparts of physical entities (PE) with automated data flows between the two [12], [17]. Computational techniques such as modelling, optimalisation and testing are used on the digital twin data to improve the physical entity. According to a recent systematic review, research on DTs started appearing in 2017 and has grown significantly since 2020, yet DT research in the maritime sector is far less prevalent than in for example manufacturing or energy research [18]. The maritime industry accounts for 80% of the world transportation resulting from trade and is considered one of the largest sources of air pollution in the world [10]. The International Maritime Organisation has set the goal to reduce total carbon emission by 40% by 2030 compared to 2008 [2], in line with the sustainable development goals (SDGs) of the United Nations [1]. Digitization of the maritime sector can provide tools to reduce emissions. Shipping 4.0 [3], characterised by coupling of physical and digital processes through data sets, has the potential to increase energy efficiency in the maritime industry [3]. Because of the extraordinary complexities of ships and shipping in the maritime industry [8], [7], digitization has been slower than for example in the manufacturing or automotive industry [10], and digitization related to logistics and operations procedures is less prevalent compared to engineering-related innovations [9]. Although maritime subsystems are digitized, there is a huge environmental potential in creating a shared platform for the different kinds of data. DTs offer means to overcome fragmentation and incompatibility of digital systems involved in ship design and operation [8]. Ludvigsen and Smogeli identify potential benefits of DT for ship owners as providing "tools for visualising ship and subsystems, qualification and analytics of operational data, optimisation of ship performance, improved internal and external communication, safe handling and increased levels of autonomy and safe decommission" [16] (p.1), all of which have environmental benefits.

To describe the level of integration between the physical and digital entity in a DT structure, Kritzinger and colleagues introduced the classification Digital Model, Shadow and Twin, where a Model has no automated data flow between the PE and digital counterpart, a Shadow has unilateral data flow from the PE to the digital counterpart, and a DT has bilateral data flow between the entities [13]. Different kinds of user interactions are possible with different levels of integration. For a digital model, the tasks will be about enabling the data flow from the PE to the model, often using sensors. With a digital shadow, a user can model and optimise based on the data flow from the PE. With a DT, a user can take corrective action with the PE itself, by sending data to it [18]. Most of the DT research on ships so far, belongs to the digital model, using the classification above [18]. We aim to conduct research in the other two, as it involves enabling actions informed by the data produced. Thus, the design challenge is to understand how DT data can be made available in a usable form for stakeholders and help automate selected operational processes in the maritime industry to reduce carbon emissions.

Integrating machine learning (ML) into MDT can be a significant step forward in enhancing the environmental sustainability and efficiency of vessels. An MDT enables the simulation, monitoring, and analysis of a ship's performance under various conditions. By incorporating ML algorithms, DTs can predict and optimize vessel operations, such as engine settings and hull painting and cleaning strategies. For instance, advanced statistical and machine learning models can be used to accurately estimate marine vessel fuel consumption—challenged by factors like engine condition, cargo weight, drafts, waves [14] and weather [20]. Similarly, it can predict the optimal timing and type of propeller and hull cleaning and/or painting that minimizes biofouling—a significant drag factor—thereby reducing the vessel's environmental impact. This technology not only aids in achieving compliance with increasingly stringent environmental regulations but also offers substantial cost savings and operational efficiencies for shipping companies. Through continuous learning and adaptation, ML-enhanced DTs promise to revolutionize maritime operations, making them more sustainable and efficient in an era of environmental consciousness.

Sustainable Human-Computer Interaction (sHCI) is a subfield of HCI that connects HCI research with the United Nations sustainability goals (SDGs) [11]. State of the art in sHCI is concerned with how to exploit emerging technologies to create interfaces and applications that can help support different SDGs. The HCI research in the project addresses the novel intersection of sHCI and Human-centred artificial intelligence (HCAI). The HCAI perspective provides methods and guidelines for creating human – AI interactions that are reliable, safe, and trustworthy [19]. In particular, the challenges of automating decision processes are vulnerable to over reliance on AI generated predictions. A HCAI inspired process can thus help ensure human-driven decision-making [19] keeping human actors in control and letting expert operators use their professional assessments in, for example, safety critical decisions. Our approach supports building on the users' tacit knowledge and experience of the problem in the design process [6], [5], and build on their familiarity with the implementation context and the real world practical challenges with systems design. Additionally, recent research from the fields of human-centred AI and medicine on AI-assisted triaging has revealed how automation of processes involves identifying how to design for control in human-AI collaboration in order to enhance rather than replace human decision-making processes [4].

2 Design case examples

We have preliminarily identified two cases where AI design tools can be used for prototyping:

Case 1: Engine configuration. Through analysing different data, it is possible to optimise engine configuration. For example, different conditions require different power output and number of engines running. Rules and regulations also set requirements on how many engines are to be used, to ensure power redundancy in safety critical situations. Simultaneously, the fuel efficiency of each engine decreases with the power output taken from the engine. There is a need for decision support for the crew running the ship, with efficient, trustworthy user interfaces. As the crew operates the ship according to e.g. professional standards for safety and customer requirements, new support for green operations must be integrated with existing system support, in a way that supports the crew´s control of the ship.

Case 2: Propeller and hull optimisation. Through selected data, it is possible to analyse live and historical data to understand the effect of maritime growth on hull and propeller, and how increased drag resulting from marine growth affects fuel consumption. Different factors affect the marine growth, such as water temperature, and how much the ship is moving through water. Varying qualities are available for antifouling paint, and the different qualities affects the requirement for cleaning frequency. The information can improve the decision making when it comes to cleaning the hull and propeller, and the types of paint that should be used. Land based decision makers and planners can use ML-based predictions to make decisions that optimise green shipping operation.

3 Conclusion

This paper has presented a design case for exploring how LLMs can provide basis for creating design artefacts to be used for developing prototypes for operators in the maritime sector, to enable them to make environmentally beneficial decisions. There is a need for interfaces to analyse outcomes of data streams originating from operating ships. We aim to understand how generative AI can help provide a basis for these prototypes. For this proposed research it is highly interesting to explore how AI-generated design artefacts such as specifications, user stories, personas, can feature in an overall research and design process.

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