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A Mission Management System for minimizing energy use and emissions during vessel operation

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A Mission Management System for minimizing energy use and emissions during vessel operation

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Abstract.
This study presents an innovative Mission Management System (MMS) designed for hybrid-powered yachts, aimed at advancing sustainable maritime operations. The MMS supports operators in optimizing total mission energy use, integrates with Energy Management System (EMS) for short-term efficiency, and addresses the shift towards supervisory control paradigms. Key components include a mission profile optimizer based on a Virtual-Vessel Model and Metamodel, real-time weather integration, and a genetic algorithm that balances user-defined priorities such as fuel consumption and emissions. In parallel, a play-based delegation system enhances human-machine interaction, allowing operators to define high-level objectives while maintaining control oversight. A dashboard interface offers progressive decision support, from manual profile definition to optimization suggestions. Three workshops with subject-matter experts validated the MMS, demonstrating its potential to reduce environmental impact without increasing operator workload, thus contributing to the transition to zero-emission operations.

1 Introduction

The maritime sector is transitioning toward hybrid and smart vessel technologies, driven by a dual mandate: reduce environmental impact and improve operational efficiency. Future yachts, for example, are expected to combine diesel engines with electric propulsion, batteries, and renewable energy sources [15]. These hybrid vessels will be equipped with advanced sensors and communication networks that enable real-time data collection, performance monitoring, and adaptive energy management.

While hardware advances enable new capabilities, they also introduce operational complexity. Managing energy flows and mission-level decisions in these vessels demands a rethinking of traditional control hierarchies. A yacht can be subdivided into four interrelated systems. The Power Management System (PMS) governs the instantaneous flow of electrical power on the millisecond timescale. The EMS, operating on the seconds-to-minutes scale, optimizes energy generation, storage, and consumption across subsystems, balancing propulsion, hotel loads, and emissions. The MMS acts as the strategic planner on the hours-to-weeks scale, aligning operations with high-level mission goals. Finally, the Human Machine Interfaces (HMIs) serve as the interface layer, enabling operators to monitor system status and intervene through dashboards and decision-support tools.

This layered architecture is exemplified in initiatives such as Feadship's Foresight program, which integrates sensor-driven decision support to help crew choose efficient routes while preserving a high-end user experience for clients [15]. However, existing approaches often require operators to directly manage low-level parameters or rely on fixed control modes, limiting the effectiveness of such decision-support tools in dynamically balancing competing objectives like fuel efficiency, emissions, voyage duration, and comfort.

Moreover, although advances in Maritime Autonomous Surface Ships (MASS) have focused on navigation autonomy, there is a critical gap in how human operators supervise mission-level planning and energy decisions in increasingly automated, hybrid-powered vessels. Most systems either lack structured support for high-level planning or assume full autonomy, neglecting the potential for effective human-machine teaming.

To address this gap, we present a novel MMS for hybrid-powered yachts that supports supervisory control. Our methodology is as follows:

1. We created a **mission profile optimizer**, described in Section 3, which uses a metamodel-based simulation of a hybrid yacht to evaluate operational scenarios and generate optimized mission plans. This optimizer balances key performance indicators (KPIs) such as fuel use, emissions, and journey time based on user-defined objectives. It leverages a virtual vessel model informed by Copernicus ERA5 weather data and a genetic algorithm for optimization.

2. A **play-based delegation framework** has been developed, introduced in Section 4, which enables operators to express intent through structured, editable plan templates—so-called "plays". These plays capture user goals and constraints, allowing the system to propose solutions and explain its reasoning. A dashboard interface supports three escalating levels of decision support: manual plan inspection, generated options and what-if analysis, and fully delegated optimization with explanations.

3. We **evaluate** this MMS concept in collaboration with subject matter experts through workshops that combined quantitative human-factors metrics with qualitative interviews, as detailed in Section 5. The results indicate that our approach enables more sustainable and effective vessel operation without increasing operator workload.

It is important to note that an optimization system is not an isolated contribution and an end by itself, disjoint from human-factors considerations. Rather, it serves as an enabler for studying human-machine interaction and supervisory control through play-based delegation. By simulating complex trade-offs in realistic scenarios, the optimizer provides a foundation for experiments with human operators and expert users.
In summary, this work contributes:

- A mission-level optimizer that integrates a digital twin and real-time environmental data to support high-level planning.
- A delegation-based supervisory control framework that enables human operators to remain in control while relying on automation for complex trade-offs.
- An operator-centered evaluation showing that such systems can support smarter, more sustainable operations aligned with MASS and smart shipping goals.

By bridging energy modeling, mission planning, and intuitive human-machine interaction, this work advances the state of the art in smart maritime systems. It offers a pathway for hybrid-powered vessels to operate more efficiently, with human operators overseeing strategic outcomes rather than micromanaging system parameters.

2 Related research
In accordance with the contributions above, we present related research on digital twins for the virtual vessel model, on existing maritime mission management systems and on supervisory control.

2.1 *Digital Twins of vessels*
Digital Twin (DT) technology has gained increasing attention in maritime and energy systems due to its potential to enhance decision-making, enable predictive maintenance, and optimize operational performance. A DT acts as a dynamic, virtual replica of a physical system, continuously updated with real-time data to reflect current states and simulate future behavior.

In the maritime sector, DTs are being explored for both system-level monitoring and full-ship modeling. Assani *et al.* [2] provide a comprehensive review of ship-specific DT applications, identifying key modeling challenges such as integration complexity, real-time data synchronization, and simulation accuracy. Similarly, Madusanka *et al.* [23] outline emerging trends in DTs for maritime operations, emphasizing their role in enabling safer, greener, and more autonomous vessels. Fonseca and Gaspar [12] discuss the data modeling challenges when creating cohesive ship DTs, highlighting the fragmentation and heterogeneity of maritime data sources. In the work of Wilkins *et al.* [42] Functional Mock-Up Units (FMUs) are introduced to manage the complexity of modeling large systems. Such an FMU platform allows for real-time parametrization, facilitating its extension into a DT environment. In a follow-up study, Dankers *et al.* [9] developed a modular platform for vessel system modeling using FMUs, representing a hybrid-(diesel/electric) powered yacht.

In broader energy system applications, Moghadam *et al.* [30] survey DT trends in power systems and identify critical advancements in modeling, control, and optimization techniques. While their focus is not exclusively maritime, many insights, such as the importance of modular simulation architectures and hybrid control strategies, directly inform the development of digital twins for hybrid-powered vessels.

Building on this literature, our approach utilizes the modular DT platform for a hybrid yacht developed by Dankers *et al.* [9] that enables real-time optimization via a metamodel within mission simulations. Rather than focusing solely on the vessel's physical systems, our digital twin supports high-level mission planning and supervisory control.

2.2 *Mission management systems*
Mission management for conventionally operated vessels has gained increasing attention as shipping companies seek to improve operational efficiency and environmental sustainability without fully automating navigation. Rather than replacing operators, MMSs increasingly aim to support decision-making through advanced simulation, optimization, and user interfaces.

Jaurola *et al.* [19] provide a comprehensive review of power management strategies for hybrid marine vessel systems, focusing on design-phase and operational energy optimization. Their work emphasizes the role of modular architectures and mission-specific operational modes, such as harbor, cruising, and station-keeping, as essential considerations when designing power systems for energy efficiency. These insights inform the integration of energy-aware planning into operational systems such as the MMS, which aims to optimize both total mission energy use and short-term power allocation.

From a broader logistics and operations research perspective, Mansouri *et al.* [25] reviews decision-support approaches in maritime shipping that balance environmental performance with operational objectives. They highlight multi-objective optimization methods that help operators consider trade-offs between cost, fuel consumption, emissions, and scheduling. These methods provide a foundation for the mission-profile optimization capabilities of the MMS, which incorporates environmental data and user-defined objectives to generate mission plans aligned with sustainability goals.

Beyond energy and efficiency, recent work by Sharif *et al.* [35] addresses the critical issue of safety in maritime routing. Their review outlines the importance of integrating safety constraints into planning tools, especially in adverse weather or high-risk navigational zones. Although their focus lies in route planning, the notion of safety as a planning parameter is also highly relevant to systems such as the MMS, which must enable operators to adjust mission profiles in response to environmental conditions and vessel limitations. The inclusion of what-if analysis and play-based delegation in the MMS supports this adaptive planning approach.

2.3 *Supervisory control*
The automation of vessel operations sets new requirements of human involvement and supervision [22]. Operator responsibilities move away from direct control and towards supervisory control, with their tasks changing from setting low-level control parameters towards setting mission profiles or high-level preferences [24]. Currently, the supervisory control solutions are based on concepts of more direct control [32, 41]. This often results in support concepts that still require constant operator attention and a high degree of expertise [5]. This limits the advantages of automated management systems, because, for example, such concepts do not reduce operator workload [40]. More importantly, these concepts do

not necessarily lead to more efficiency and safety as operators do not receive the support they need to transition from direct control to supervisory control causing them to micro-manage, distrust the offered systems, or make wrong decisions due to a lack of situational awareness. Supervisory control concepts are needed that allow operators to enact control over management systems in an effective, safe, and efficient manner.

Delegation refers to situations where one actor has managerial authority over another but does not command every aspect of task performance [26]. Through delegation, the captain can express their intent to a vessel management system, which then interprets, completes, and produces precise plans for this intent while updating the captain on its progress. Consequently, the effectiveness of operations relies less on manual control, intuition, and past experience in accommodating multiple objectives, and more on the clarity of the captain's intent, the system's interpretation and implementation of this intent, the justification for its proposed options, and the communication between parties. Some purported benefits of delegation include the reduction of mental workload for human operators, even in unpredictable environments, the formation of shared understanding and expectations between human and systems, streamlined communication and increased collaboration fluency, which arguably enable operators to exercise Meaningful Human Control [31, 11, 27, 8]. Delegation methods have been mostly applied in the military domain [29, 39] and applications that touch on the maritime domain are, to the best of our knowledge, currently limited to applications in the Navy [3].

Different delegation concepts can be envisioned depending on the degree of supervisor involvement or, dually, reliance on automation [6, 28]. It is therefore important to (i) properly translate levels of supervisory control into concrete mission management functionalities and human-machine teaming protocols and (ii) understand which level would be preferable, especially in terms of concrete human factors metrics such as usability, mental workload, transparency, trust and intended reliance.

3 Mission profile optimizer

The first key component of the MMS is the mission profile optimizer, which determines optimal operational parameters based on user-defined objectives and constraints. The optimizer comprises six components: (1) the virtual vessel model, (2) its metamodel, (3) mission profile definitions, (4) the simulator, (5) the optimization algorithm, and (6) play-based delegation. The relationships between these components are illustrated in Figure 1, and the following subsections provide detailed descriptions of each, with the exception for play-based delegation, which is discussed separately in Section 4.

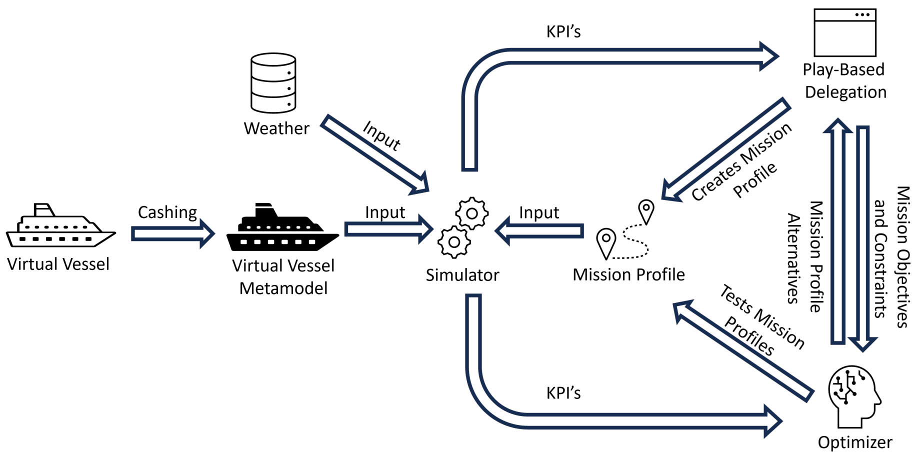

Figure 1: The architecture of the mission profile optimizer.

3.1 Virtual Vessel

An FMU-based modular DT of a hybrid yacht has been developed to represent the vessel powertrain. In this study, a forward-backward facing modeling approach is used. This simulation regime involves forward-facing causality of calculations beginning at the prime mover in the direction of the propulsion. Moreover, the forward-backward simulation approach deals with quantities that are physically measurable in the vessel, satisfying the requirement for DTs [38]. The FMU-based virtual vessel allows for design modularity and integration of user-specific vessel configurations. The MMS utilizes a model of a hybrid diesel-powered yacht, incorporating engines, generators, batteries, and auxiliary systems to manage hotel loads. An overview of the digital yacht Power, Propulsion, and Energy (PPE) system use-case is provided in Figure 2. As shown, the model features four engine/generator sets, two battery packs, and two combined Power Take-In and Power Take-Off systems.

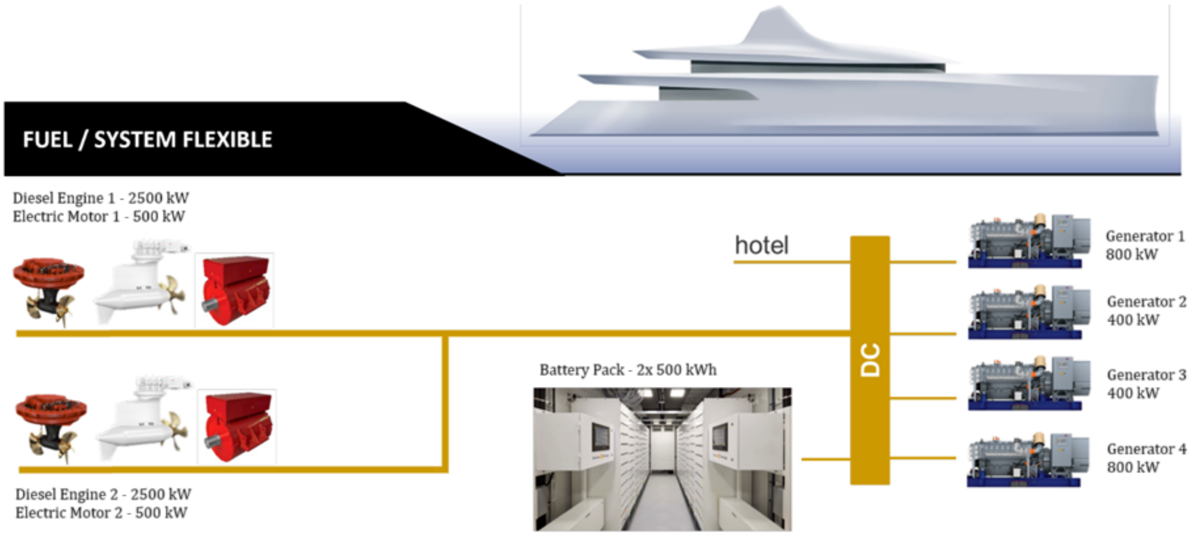

Figure 2: PPE system of the studied digital yacht use case.

The EMS manages system configuration and overall power distribution. Based on speed requests or hotel load demands, the EMS can switch diesel or electric engines on or off as needed. A modified Equivalent Consumption Minimisation Scheme (ECMS) approach is used to minimize the overall losses in power delivered to the propulsion and auxiliary systems to minimize the overall fuel consumption [34]. It utilizes available power sources through various operational modes, which also help determine the auxiliary load requirements. The EMS supports multiple operational modes, including high/low-speed sailing, maneuvering, dynamic positioning, harbor mode, shore converter mode, and emergency mode. For the purposes of the MMS, these modes are simplified into two categories: electric and hybrid.

The exact workings of this virtual vessel model are too detailed to fully describe here. We refer to Dankers *et al.* [9] for more details on how the virtual vessel translates energy estimations and the translations to emissions.

3.2 Virtual Vessel Metamodel

Ideally, the virtual vessel is used directly for running simulations. Its execution speed is however too slow to support optimization effectively. Therefore a metamodel is created; constructed in this case by caching results in steps, and interpolating between the steps. The inputs and outputs of the metamodel are presented in Table 1. Please note that the battery State Of Charge (SOC) is not allowed to be below 30% in order to always be able to enter a harbor and in practice it never reaches 100% charge level.

Input	Unit	Step size	Range	Output	Unit
Battery SOC	%	10	30-90	Total NO_x pollution	kg
Battery target SOC	%	10	30-90	Total CO_2 pollution	kg
Electric or hybrid	bool	1	0-1	Final battery state	%
Initial speed	m/s	1	1-12	Final ship speed	m/s
Target speed	m/s	1	1-12	Total time needed	s
				Total distance traveled	m
				Total diesel consumption	tons

Table 1: The inputs and outputs of the metamodel.

The vessel travels a straight 10 km path under ideal conditions, with a perfectly calm sea state. While factors such as currents and weather impact the resources needed for the journey, these are not currently modeled within the virtual vessel. As a result, the output from the model would have to be scaled to account for these influences. As this scaling is not trivial, we chose to keep it simple by applying a linear increase in CO_2, NO_x, and diesel consumption based on wind speed.

3.3 Weather

To account for weather in mission planning, a weather service should be used to retrieve localized and accurate forecasts for the duration of the upcoming mission. While integrating such a service is straightforward for the developed proof-of-concept, we have opted to use a historical weather database to ensure reproducible results. For a given reference date in the past, we treat the recorded weather as a forecast.

The weather data is sourced from the Copernicus Earth Observation Program ERA5 [17]. It contains detailed location and time resolution, which allows for more refined analyses and additional functionality in the future. ERA5 data includes information on location, time, precipitation, temperature, and wind speed. Weather information is retrieved based on latitude, longitude, and time for each route segment.

3.4 Mission Profile

The mission profile outlines the journey and serves as input for testing in the simulator. It may either be (partially) defined by the user, or created by the optimizer when searching for an optimal mission profile.

The mission profile consists of a user-defined route, using waypoints and doing justice to the Earth's curvature. Each segment is characterized by three parameters: (1) the target speed, (2) the target battery SOC, and (3) whether electric mode should be used. Additionally, the mission profile includes a reference date for the journey's start, as well as the vessel's initial speed and battery SOC.

3.5 Simulator

The simulator calculates four Key Performance Indicators (KPIs) for a mission profile: (1) Fuel consumption, (2) Time spent, (3) Tail-pipe NO_x emission, and (4) Comfort.

The first three KPIs are directly derived from the virtual vessel metamodel (see Table 1). The simulator operates deterministically, essentially moving the ship along the desired route and records the outcomes. Each segment of the mission profile is divided into 10 km chunks. For each chunk, the KPIs are calculated and accumulated, yielding the final scores for each category. For chunks smaller than 10 km, the results are scaled linearly.

The comfort KPI is a composite of several factors, and in our implementation includes wind speed, temperature and precipitation. The current formula, as presented in eq:(1)-eq:(3), is used in this study to illustrate how comfort can affect the results, but requires more work to be included in a real system (e.g., including cargo status for other type of vessels). As the overall problem is a minimization problem, a value of 0 is the best score, and a value of 1 is the worst possible score.

Weather information is sourced from the historical Copernicus ERA5 database. While this enables realistic environmental modeling, it assumes perfect foresight of future weather conditions. In a practical setting, however, future weather is uncertain. Incorporating this uncertainty into the simulator and, specifically, into the comfort KPI is a direction for future work. For instance, forecast variability could be used to penalize overly optimistic comfort predictions or to adjust route planning under risk.

In eq:(1) the wind comfort of a journey segment is calculated. The value is scaled between 0 and 1 by using the minimum and maximum wind speeds for that location and time (as found in the ERA5 database) while performing the optimization.

$$windComfort_{segment} = \frac{(windSpeed_{max} - windSpeed_{segment})}{(windSpeed_{max} - windSpeed_{min})} \tag{1}$$

In eq: (2) the temperature component of the comfort score is calculated. The temperature is evaluated in categories; comfortable, neutral, and uncomfortable.

$$temperatureComfort = \begin{cases} 0, & \text{if } 18 \leq temperature \leq 22 \\ 0.5, & \text{if } 10 \leq temperature < 18 \quad || \quad 22 < temperature \leq 30 \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

Precipitation comfort works analogously to wind comfort, and is shown in eq:(3).

$$precipitationComfort_{segment} = \frac{(precipitation_{max} - precipitation_{segment})}{(precipitation_{max} - precipitation_{min})} \tag{3}$$

The wind, temperature and precipitation are averaged to arrive at an integral comfort score for a single segment. The comfort scores for each segment of a route are combined to form the comfort KPI of the entire mission profile, taking into account the length the segments.

3.6 Optimizer
The assigned weights are used to optimize a given mission profile using a Genetic Algorithm (GA) [1]. A GA is an algorithm inspired by nature, particularly the concept of evolution. A population of potential solutions is evaluated based on their performance in the given task. The most fit solutions are more likely to reproduce, meaning they pass on their genetic information to the next generation. Combined with crossover and mutation operators, new generations are created until a stopping criterion is met.

An individual is defined by its genes, which in our case correspond to the mission profile segment parameters being optimized: (1) the target speed, (2) the target battery SOC, and (3) whether electric mode should be used. Additionally, each individual includes the reference date for the journey's start (see Subsection 3.4). Although it is technically possible, the route itself (a series of latitude-longitude coordinates) is not altered by the optimizer. This decision was made because there are sufficient systems that perform route optimization [21].

The goal of the optimization is to minimize a weighted sum of the following KPIs: (1) Fuel consumption, (2) Time spent, (3) Tail-pipe NO_x emission, and (4) Comfort (see Subsection 3.5). The user can reorder the four KPIs in any order on the dashboard and can also remove KPIs from the list. The final result is translated into a set of weights for each KPI. On the dashboard, preferences and constraints for the KPIs can be set, which are then translated into weights for each KPI.

A key challenge is that the four KPIs do not use the same scale or units. For instance, how should an additional kilogram of diesel be compared to saving 10 seconds of the entire journey? We employed a simple yet effective solution. During optimization, many mission profiles are tested, providing lower and upper bounds for each KPI. For a short mission, these values are low, while for a transatlantic crossing, they will be much higher. Each individual in the population is scored relative to these bounds. For example, the fastest solution scores 0 on the time KPI, while the slowest one scores 1. The mission profile with the lowest fuel consumption scores 0, while the highest one scores 1, and so on. This strategy standardizes the different scales and units, while remaining agnostic to the specific mission being tested.

The optimization process can be broken down into two key functionalities. The first functionality aims to achieve the best possible fitness according to a specific set of KPI weights. These weights are considered fixed in this first phase of the optimization. It may be difficult for humans to clearly define their goals as a set of specific weights [36]. Powell refers to this challenge as “goal uncertainty” [33, Ch. 10], describing it as: “Arises in problems with multiple competing objectives, where the decision maker's preference between those objectives is uncertain, or when some objectives are not articulated”. The second functionality addresses this goal uncertainty by widening the search area using dynamic novelty search [14]. This approach guides the algorithm to unexplored areas of the fitness landscape. The algorithm, called Fitness Diversity Driven Co-Evolution (FDDC) [13], works with a secondary GA whose genes consist of the KPI weights. By allowing this algorithm to adjust the weights of each KPI, the outcome is a set of solutions that prioritize different KPIs in varying degrees.

GA solutions of both functionalities can be visualized on a Pareto front, a collection of solutions that are not dominated by any other solution [18]. By visualizing the Pareto-optimal solutions, the end user can select the solution they prefer, while understanding the trade-offs involved in choosing one solution over another. For an example, see Figure 3. To further stimulate the advancement of the Pareto front, some of the current Pareto solutions are injected into the parent selection process at each generation. This also helps maintain genetic diversity within the population, increasing the robustness of the algorithm.

To improve the explainability of the GA, we have implemented a contrastive explanation feature. Each KPI of a solution is compared to the entire pool of found solutions. For example, the time it took for a particular solution to reach its destination might be in the top 10% compared to other solutions, while its tail-pipe NO_x pollution could be in the top 60%.

4 Play-based delegation for supervisory control
The second key component of the MMS is play-based delegation for supervisory control. We mapped MMSs functionalities to levels of supervisory control, using expertise on delegation. Various delegation methods have been identified, based on the interaction between the delegating and delegated agents [6]. These methods span a spectrum of operator involvement and reliance on automation, with *play-based delegation* striking a middle ground. A play is an adjustable plan template that allows operators to specify high-level objectives, resources, (hard) constraints, and (soft) preferences [26, 37, 39]. For

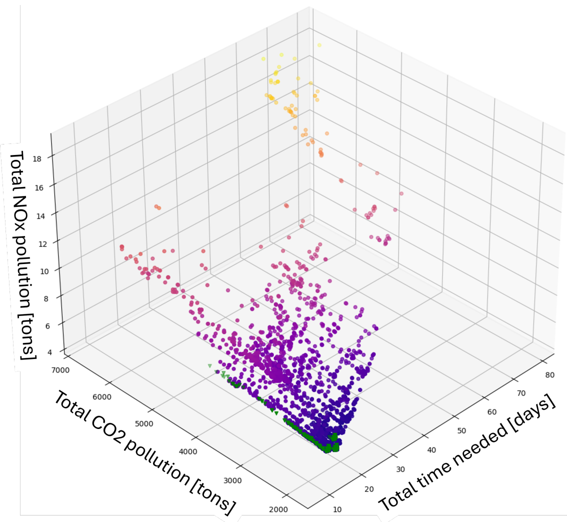

Figure 3: Pareto front for an example mission, that balances time for the journey, tail-pipe NO_x and CO_2 pollution. The green triangles are the front itself. The coloring corresponds with tail-pipe NO_x pollution to make the visualization more interpretable. Comfort is not visualized, but does contribute to whether mission profiles lie on the Pareto front.

example, during play-based delegation, captains may use a user interface to create plays, resulting in constraints and preferences for the upcoming mission. Constraints are hard, such as declaring a fixed arrival time, while preferences are soft, such as reducing emissions as much as possible while ensuring the cheapest plan. The system proposes options and explains how these comply with the given guidelines, without being dominated by other candidate solutions.

A dashboard interface was developed, offering three levels of decision support, progressively ranging from simple to complex interactions, namely (1) *Overview*, (2) *Mission Profiling*, and (3) *Smart Support*. The different levels of control and decision support were operationalized as different tabs of an interactive dashboard. That is, each tab of the dashboard represents another level of decision support.

The (1) *Overview* tab allows the operator to manually define a mission profile, calculate its KPIs by the simulator, and inspect basic information about the results and vessel components. This mission profile assumes the current date as starting date for the journey (i.e., a fixed date in the past in the ERA5 database). For reasons of brevity, we have omitted this figure.[1] It is similar to the mission profiling tab (Figure 4), except that it does not have the options for setting the environment conditions (upper left in Figure 4), and does not include details on the KPIs for the generated options (lower right of Figure 4).

The (2) *Mission Profiling* tab, as shown in Figure 4, proposes options complying with the user-defined profiles, reports on their performance against the several KPIs, and allows the user to vary the weather conditions in a what-if analysis. The temperature and head wind can be set to chosen values, which impact the comfort and fuel efficiency of the journey. A given mission profile can then be simulated, assuming these conditions. Currently, the conditions are taken to be constant for the entire journey; a point of improvement would be to be able to vary this for each section of the journey.

The (3) *Smart Support* tab enables the operator to define the priority of the KPIs by ordering them (the left part of Figure 5), which translates to a set of weights for the optimization. In addition, target departure and arrival dates can be set. The optimization calculates options which are displayed to the user as a Pareto front (see separate Figure 3). On the bottom right of the screen, the textual explanation functionality provides insight into a found mission profile (the right part of Figure 5). A complete overview of this tab has been omitted as the text would become unreadable.[1]

5 Demonstration and evaluation

We conducted three workshop sessions where domain experts evaluated the MMS and its dedicated human-machine interface. The gathered data were used to collect insights on research questions of

[1] Please see `http://schadd.com/Papers/MENENS_dashboard_step_by_step.pdf` for more detailed figures.

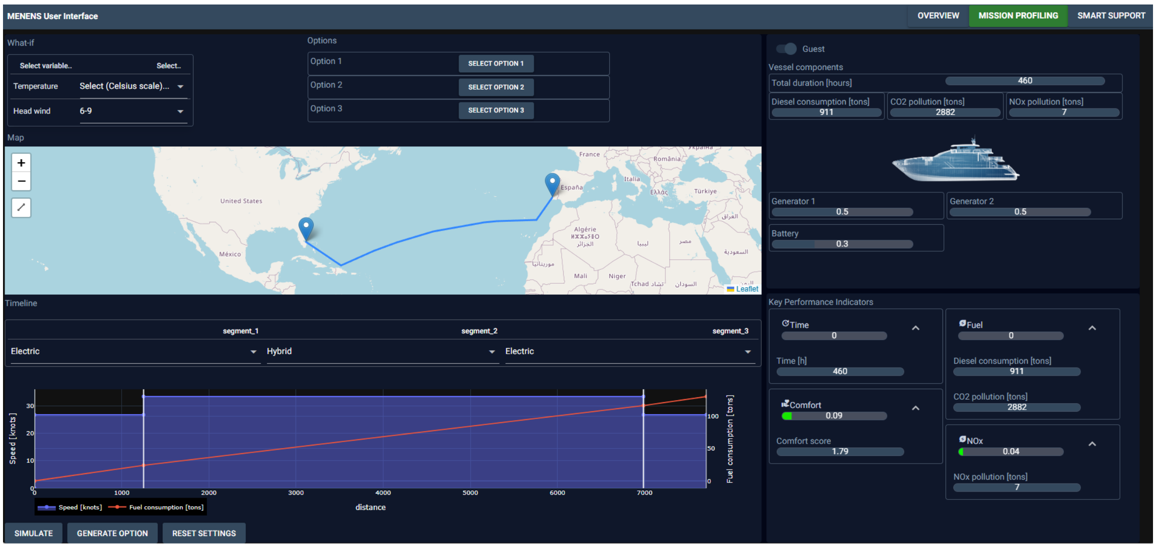

Figure 4: The second level of decision support to the operator, proposing options and allowing a what-if analysis on varying weather conditions.

interest: (i) Which level of decision support is preferable for vessel operations, in terms of usability, trust and intended reliance, transparency, and mental workload? (ii) To what extent is the tool generalizable to vessel operations beyond the yacht use-case?

5.1 *Study population*
Eleven participants were recruited from the industrial partners of TNO in the MENENS consortium. The inclusion criteria were: (i) familiarity with vessel operations as R&D experts or operators, (ii) English language proficiency, and (iii) interest in automation and decision support. All participants had experience in maritime R&D, combined, in at least two cases, with experience as vessel staff.

5.2 *Procedure*
A workshop session consisted of four phases: (1) Introduction: The facilitator briefed the participants on the scope and choices made for the development of the MMS and presented the overarching goal and procedure of the workshop. (2) Tutorial: The facilitator walked the participants through the three tabs of the interactive dashboard, with the help of a simplified scenario of a transatlantic crew-only operation. In particular, the facilitator sketched a situation in which a yacht captain receives the mission statement to reach a destination as fast as possible and as fuel-efficiently as possible to pick up new clients, but following a pre-determined route, due to safety and logistical reasons. The storyline was such that the mission takes place in a region and time of the year where extreme weather conditions are less likely, but the weather conditions are still volatile – therefore it is important to safeguard the operation for different environmental conditions. In general, the storyline was such to encourage the consideration and responsible use of the functionalities offered by the tool. For each tab, once all input fields were completed, the corresponding output of the system was displayed. (3) Runtime: The participants went through each tab again, using the same background storyline but an adapted mission statement (e.g., a mission statement concerning a *guest* operation, requiring a different ranking of priorities, safeguarding against weather conditions, justification for the selected option). This was to nudge the participants to experience even more functionalities of the tool. After trying out each tab, a questionnaire was launched, targeting usability, trust and intended reliance, transparency, and mental workload (inspired by [4, 7, 16]) to assess the experience of the participants with both the functionalities and design protocols of the tab in question. (4) Interview: In a semi-structured, plenary interview, participants provided feedback on the added value of the tool, used to elucidate the responses to the questionnaire items.

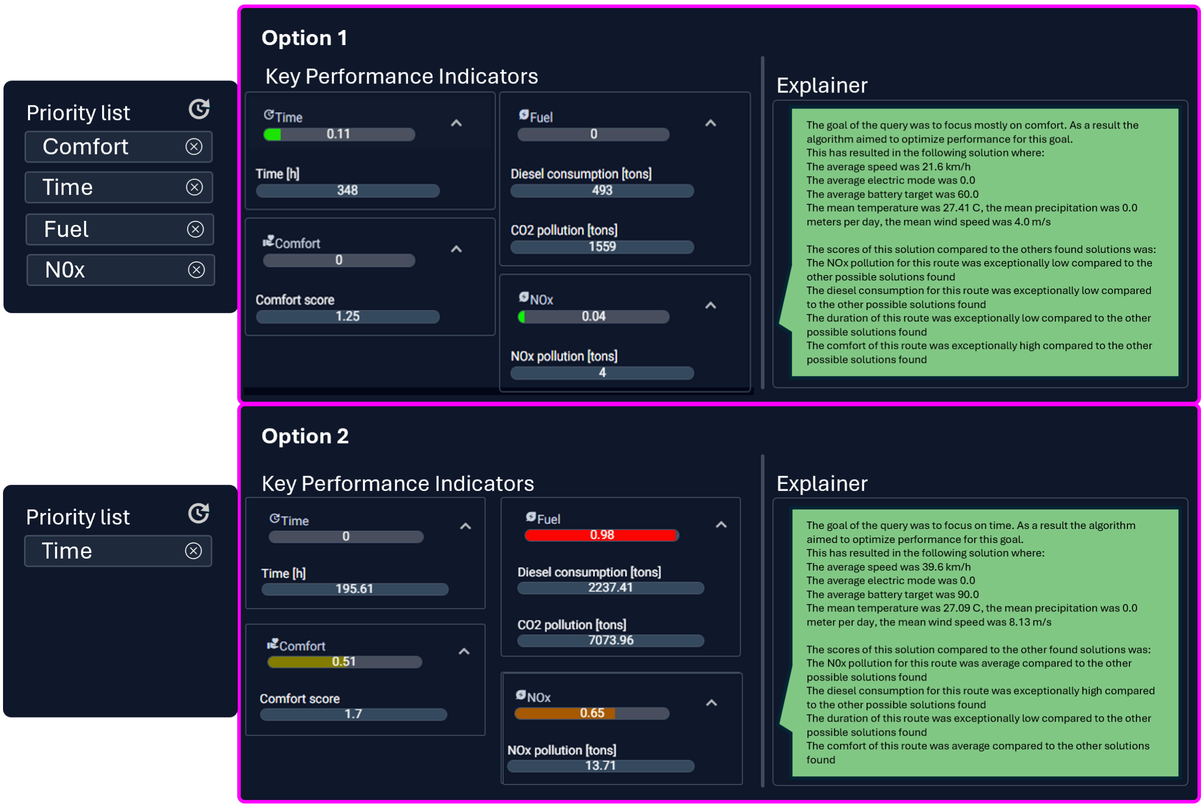

Figure 5: The third level of decision support to the operator, allowing the system to propose mission profiles based on different user-defined KPI preferences and explain why a certain option was proposed.

5.3 *Results*

The quantitative results in terms of the overall usability, trust, workload, and transparency scales are presented in Table 2. All three levels of decision support were mostly positively evaluated with respect to usability and mental workload and neutrally with respect to trust and transparency. However, only minor differences can be observed between the assessments for each level of decision support (Table 2). Due to sample size (n=11), no statistical tests were run. The participants did report that they expected the Smart Support tab to be the level of decision support envisioned for a final product.

We processed the qualitative responses of the participants to the open feedback fields of the questionnaires and the verbal feedback from the semi-structured interview. Regarding the first research question on the preferred level of decision support, the key findings can be summarized as follows:

1. The difference in decision support levels between the tabs is certainly perceivable, which is instrumental in understanding which level of support would be most suitable and for which purposes.

	Usability			Trust			Transparency			Workload		
	tab 1	tab 2	tab 3	tab 1	tab 2	tab 3	tab 1	tab 2	tab 3	tab 1	tab 2	tab 3
Mean	3.6	3.2	3.2	5.7	5.8	5.7	5.7	4.5	4.9	3	2.9	3.4
Median	3.8	3.4	3.3	6.0	6.0	5.6	5	4.5	4.7	3	3.0	4.0
SD	0.7	0.8	0.8	1.9	1.6	2.0	2.3	2.2	2.3	1.3	1.1	1.2

Table 2: Statistics for the overall usability, trust, transparency, and mental workload scales (tab 1 := Overview, tab 2 := Mission Profiling, tab 3 := Smart Support). Usability items were rated in a 1-5 Likert scale (fully disagree to fully agree), trust and transparency items with a slider from 0 - 10 (Not at all - Very), and mental workload with a 1-7 Likert scale (Very Low - Very High).

2. The layout is clear and intuitive and everyone can master this software quite quickly, aided by the progressive familiarization with MMS features across the different tabs. This probably contributed to the mostly favorable evaluations with respect to usability and workload.

3. The comparative benefits to commercial route optimization tools include: possibility to select a mode in defining mission profiles, the *multi*-objective optimization, the brief natural language explanation justifying system-generated options, and the ability to run multiple scenarios quickly.

   Interestingly, while these features were generally well-received, they did not necessarily translate to higher ratings for transparency and trust (as could be, at least theoretically, expected given the role of explainability as facilitator of trust [10]). Upon further inquiring into this and the potential improvements in MMS functionalities and interaction design in this direction, some participants revealed that they would have liked the option to further inspect the mechanisms underlying the MMS decision-making (e.g., the accuracy of outputs of the virtual vessel meta-model, physics-related assumptions behind the calculation of KPIs such as Comfort, the vessel's characteristics and equipment status). While some of these concerns could be attributed to the early-stage prototype that was used for demonstration purposes, a more significant insight emerged, especially from participants with operational experience: that the maritime domain tends to be more conservative in adopting such automated systems despite their apparent benefits (which can also be witnessed in other initiatives [19] and could be explained, from a cognitive standpoint, in terms of naturalistic theories of expert decision-making and dual-process theories of reasoning [20]). Specifically, captains often rely on their own intuition and experience and thus desire more insights into the workings of the MMS to ensure they align with their own, which could seemingly be at odds with usability and workload considerations. The key-takeaway was to clearly distinguish the training and operational use phases: it is likely that developing more functionalities, e.g., tab variants varying even more in the amount of displayed information, could help users suitably calibrate their trust during training, even if the final adopted system offers a more streamlined, high-level decision support interface that still harvests the usability and workload benefits.

4. The Smart Support tab should be intended as the final product in the future, provided that certain improvements are implemented. However, the other two tabs could be useful for (a) research purposes, (b) as part of the training and adoption phase, e.g., to progressively familiarize with the MMS, and thus gain understanding and trust in the system.

Regarding the second research question, on the generalizability of the tool beyond the yacht use-case, participants indicated that it should be in principle possible to apply the MMS architecture and interaction concept when adopting alternative vessel configurations. However, that would entail some modifications, e.g., in the production of the virtual vessel meta-model as well as in the interface, to allow users to specify different types of vessels and fuels. Most importantly, the objective of Comfort would have to be individuated differently across different vessel types and be reshaped into its conceptual analogues (e.g., 'cargo status' for cargo vessels, 'crew habitability' or 'workability' for Navy vessels, etc.) which naturally entails adjusted calculation mechanisms.

6 Discussion and Conclusion

This study presented a novel MMS designed to support hybrid-powered yachts in achieving more energy-efficient and sustainable operations. By integrating mission-profile optimization with real-time weather data, a virtual-vessel metamodel, and a genetic algorithm, the MMS allows operators to define and evaluate operational strategies aligned with environmental and operational goals. The system's capability to balance key performance indicators such as fuel consumption, emissions, and travel time—based on user-defined priorities—provides tailored decision support across a wide range of missions.

A key contribution of this work is the development of a play-based delegation framework that shifts the operator's role toward supervisory control. By offering a layered interface with increasing levels of support—from manual input to automated suggestions—the MMS empowers users to maintain strategic oversight while leveraging automation for complex optimization tasks. This approach not only reduces cognitive workload but it can, under certain conditions, also enhance trust and transparency in system recommendations.

The MMS was validated through expert workshops, which confirmed its potential to reduce environmental impact without compromising operational effectiveness or increasing operator workload. The combination of mission-level planning and real-time adaptability positions the MMS as a promising solution for the maritime industry's ongoing transition toward zero-emission operations.

Building on the proof-of-concept, future research will explore four key directions to enhance and broaden the impact of the MMS: (1) While the current MMS is tailored to hybrid-powered yachts, future work will adapt it to other vessel categories. This involves reconfiguring the virtual vessel model to reflect different propulsion systems, operational profiles, and mission objectives, as well as enriching the dashboard interface, consistent with the suggested modifications emerging from the workshops. (2) Extending the MMS to include real-time synchronization with onboard sensors and systems, enables continuous performance monitoring and adaptive mission re-planning during operation. (3) Improving the precision and scope of the simulations remains a priority. Incorporating dynamic behavior under various sea states will improve the accuracy of the model. We furthermore want to account for uncertainties in metocean data, such as forecast errors in wind, waves, and currents by using techniques such as probabilistic modeling and ensemble forecasting. (4) The MMS framework shows potential for use in early-stage vessel design. Designers can assess trade-offs by simulating and optimizing mission profiles. This integration would allow mission-based performance evaluation to inform key design decisions from the outset. Together, these research directions aim to evolve the MMS into a versatile, scalable, and industry-ready system that supports sustainable maritime operations across a wide range of missions.

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