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ADVANCEMENT IN WIND OPERATION SESSION

Hybrid Decision Support System for Improved Offshore Operation Planning

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D-ICE ENGINEERING

1. Abstract

Operational requirements are more and more demanding for all vessels but this is particularly true for dynamically positioned ships.
The progressive entry in force of new regulations towards carbon-free emissions combined with the market shift towards renewable energies such as offshore wind result in many additional constraints. The complete mastery of the ship from its physical behaviour to its environmental footprint is now compulsory. However, the physical phenomena related to offshore operations are very complex resulting in a lot of unknowns. In addition, from weather forecast to signal sensing, all data are subject to uncertainty and inaccuracies.
In this paper, we present a new approach combining large-scale simulation plans and in-situ recorded data to be able to cope with the inherent stochasticity of marine environment and ship dynamics to be able to provide the operator with safe and solid decision support.

2. Challenges

2.1. General Introduction

The development of decision support systems onboard ships is not only important but also indispensable for a multitude of reasons. These systems play a pivotal role in enhancing the safety, efficiency, and sustainability of maritime operations, making them an imperative investment for the industry. Here are key reasons why they are so vital:

1. **Safety at Sea**: Ensuring the safety of those at sea, especially in hazardous weather conditions, has always been the foremost concern of marine professionals. Decision support systems can provide help to navigate vessels safely through adverse conditions, preventing accidents and protecting lives.

2. **Environmental Conservation**: Marine ecosystems are not just essential for the maritime industry; they are critical to the health of our planet. These ecosystems play a crucial role in processes like CO2 regulation, making their preservation paramount. Decision support systems can aid in minimising the environmental footprint of maritime operations by optimising routes, reducing emissions, and avoiding sensitive areas.

3. **Operational Efficiency**: In an era marked by economic crises, inflation, and fluctuating raw material costs, the ability to master and optimise operational costs is fundamental for the viability of maritime businesses. Decision support systems have a direct impact on reducing overall expenditures.

4. **Resource Management**: The demanding nature of maritime operations places considerable stress and pressure on crews and operators. Decision support systems serve as invaluable tools in assisting operators, allowing them to focus on their core responsibilities while automating routine tasks and providing critical insights. This not only improves efficiency but also enhances crew well-being.

5. **Emergency Response**: As ships and maritime systems become increasingly complex, there is a growing need for sophisticated emergency response capabilities. Decision support systems are at the forefront of this development, offering additional ways to manage emergencies effectively. They provide real-time information, scenario simulations, and contingency plans to respond to unexpected situations swiftly and efficiently.

The implementation of decision support systems onboard ships is therefore not just a technological advancement; it is a strategic imperative.

These systems are integral to safeguarding lives, preserving the environment, optimising operations, alleviating stress on crews, and ensuring effective emergency responses in an ever-evolving maritime landscape. For example, According to the DNVGL-ST-N001 standard, weather monitoring systems increase the workability by a factor between 10% and 20%.

2.2. Focus on Dynamic-Positioning Operations

The significance of decision support systems (DSS) becomes even more apparent within the realm of Dynamic Positioning (DP) operations. DP vessels, by their very essence, are complex entities navigating within demanding environments, composed of an intricate web of systems and subsystems intricately interconnected.

Furthermore, offshore wind operations introduce a myriad of additional challenges, including but not limited to:

1. **Adverse Conditions**: Offshore wind farms are typically located in regions susceptible to strong and turbulent winds, often accompanied by relatively shallow waters compared to traditional oil and gas (O&G) operations. This characteristic leads to frequent encounters with intricate and hazardous environmental conditions.

2. **Heightened Collision Risks**: Wind farms inherently introduce more obstacles and potential hazards compared to the open sea. The close proximity of multiple wind turbines and substructures elevates the risk of collisions and operational mishaps.

3. **Increased Operational Frequency**: Offshore wind energy operations demand a heightened volume of daily marine activities due to the frequent repositioning required in proximity to the wind turbines. Although individual operations on a wind turbine may be shorter than those on a conventional platform, the cumulative number of daily operations substantially increases, resulting in a surge of vessel approaches and potential operational complexities.

Conventional methods for planning and executing operations predominantly rely on the utilisation of capability plots, a well-established tool for analysing operational constraints and boundaries [insert reference]. However, one of the most significant drawbacks of capability plots lies in their dependence on mathematical models and static considerations.

To mitigate this limitation, time-domain simulations have emerged as an alternative approach. While this enables more sophisticated modelling of environmental conditions and the utilisation of advanced mathematical models, it remains primarily theoretical. The challenge of accurately resolving the complexity of the problem continues to be a focal point of ongoing research, especially in light of the unresolved Navier-Stokes equation, which remains an enduring challenge.

Moreover, as elaborated in the Pivano paper, achieving good results necessitates meticulous adjustment of numerous parameters within the mathematical models. This process is a demanding and resource-intensive endeavour, requiring intricate mathematical computations, keen attention to detail, and a profound understanding of the underlying physics and mathematics.

It entails extensive testing, often entailing numerous iterations, and frequently adopts a trial-and-error methodology to pinpoint optimal parameters. Errors in parameter adjustments can result in inefficiencies or safety hazards, underscoring the imperative need for scrupulous and cautious handling of this task. Additionally, it requires utilisation of collected data under specific environmental conditions which poses a challenge, given the stochastic nature of marine environment.

Additionally, the simulation plans cannot cover the entire cases the operators will see in real life scenarios including weather distributions, alteration in any propulsion systems, tuning of the DP system, etc.

To cope with the cost and burden of this process, the continuous incorporation of real-time data collected during operations used in combination with theoretical simulations can provide a practical solution.

3. PREDICTiCS: A Novel Decision-Support Framework

PREDICTiCS aims at supporting marine operation planification by providing a prediction of the ship's behaviour under specific weather conditions. Earlier works conducted at D-ICE Engineering allowed us to define a unified framework for floating body and vessel control simulation [2].
At the same time, a variety of machine-learning based approaches have been proposed by researchers to leverage the data that is becoming more and more available[3]. Those models offered better insights on the influence of various parameters on vessels' fuel consumption, but not so much on operation planification and predicting the future.
With PREDICTiCS, we propose a novel hybrid framework combining physics-driven and data-driven approaches to assist in operation planification by leveraging simulated and empirical data.

3.1. Design Philosophy

PREDICTiCS is designed to work in cooperation with a dynamical positioning system following the 7 pillars principles of Low Risk DP Operations.

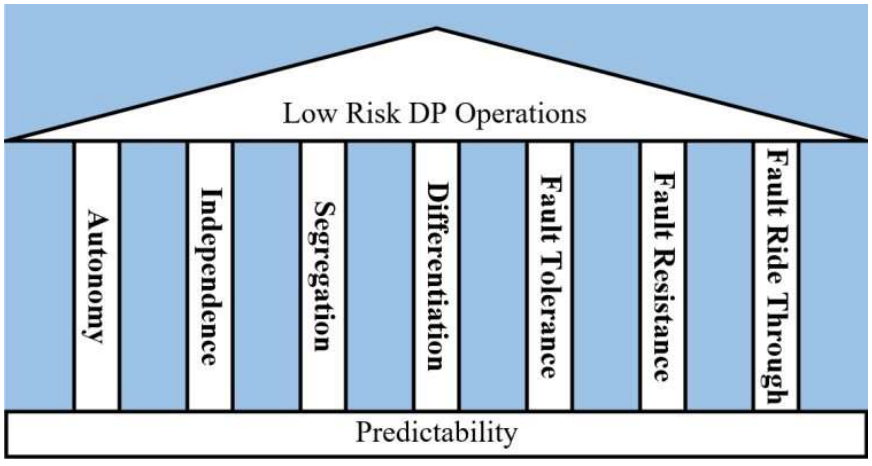

Figure 1 - Low Risk DP Operation 7 pillar principles

Applied to PREDICTiCS, these considerations give rise to the following set of requirements:

1. **Autonomy**: The system should operate independently on its dedicated hardware, ensuring self-sufficiency.

2. **Independence**: PREDICTiCS should maintain no direct connections with critical low-level automation devices to prevent interference or disruption.

3. **Segregation**: There should be only one read-only connection between PREDICTiCS and the DP (Dynamic Positioning) system. This connection should exclusively involve the sharing of recorded data that remains independent from ongoing DP operations.

4. **Differentiation**: PREDICTiCS and the DP system should utilise physically separated devices and robust network protection measures to ensure clear boundaries and prevent unintended interactions.

5. **Fault Tolerance**: Any malfunction or failure within the PREDICTiCS system must not impact the operational integrity or health of the DP system or its network.

6. **Fault Resistance** Utilise hardware that adheres to rigorous marine quality standards, such as DNV (Det Norske Veritas) approval, to withstand the demanding maritime environment.

7. **Ride Through**: Ensure the capability to recover data from scratch at any given time, offering the system the resilience to continue functioning seamlessly.

Additionally, recognizing the unique nature of a decision support system, the following requirements are introduced:

8. **Clarity** PREDICTiCS should provide operators with clear, straightforward insights and operational guidance. Given its potential use during critical situations, the system's communication should be simple, precise, and easily comprehensible.

9. **Transparency**: While the advice offered by PREDICTiCS may not always be optimal, the system must be capable of providing feedback and rationale behind its recommendations. Maintaining trust with operators is essential, and the ability to furnish explanations enhances transparency.

10. **Integrity**: PREDICTiCS should consistently produce reliable and high-quality output. In cases of suboptimal performance or anomalies, it should facilitate the identification of root causes. Automated learning within the system should consistently enhance its quality without resulting in degradation.

These requirements collectively form a robust framework that addresses the autonomous and independent operation of PREDICTiCS, safeguarding its performance and reliability in dynamic maritime operations while ensuring clarity, transparency, and ongoing improvement in decision support capabilities.

3.2. Software Architecture

The PREDICTiCS framework is then divided into two distinct parts:

- A real-time component that continuously updates its previsions using live data from the ship's database. It provides predictions through a REST API[1].
- A dashboard UI[2] that connects to this API and presents the operator with clear predictions as decision support.

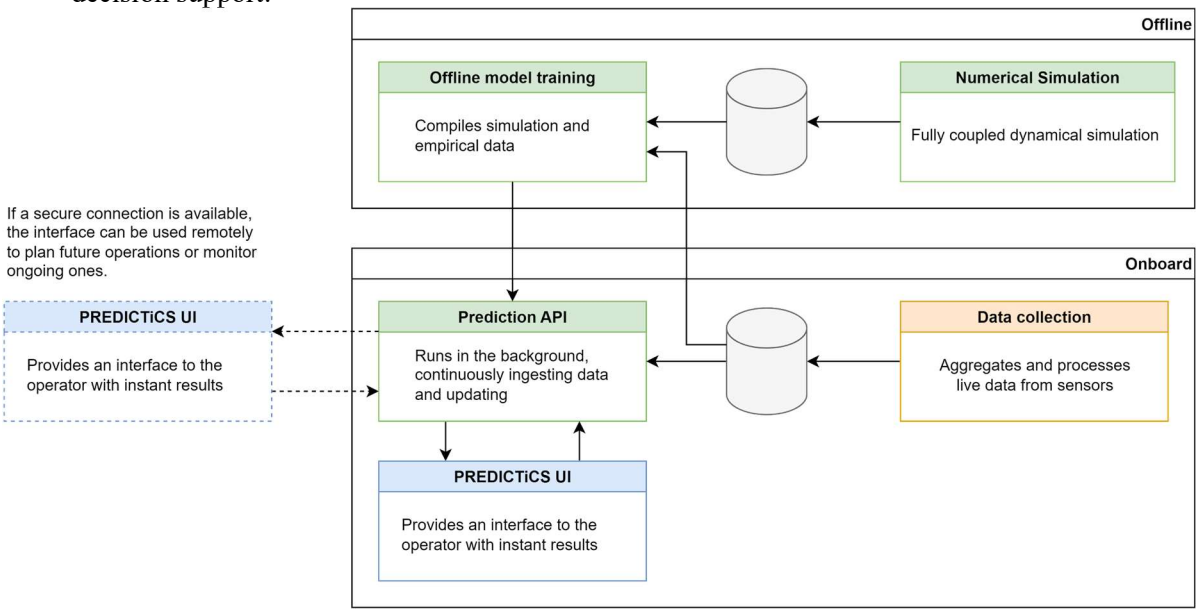

Figure 2 - System diagram of the software architecture

This architecture allows flexible calls. Theoretically, it can be executed from any network-connected location (Typically making it possible to have it remotely if a connection to the ship is available - making operation planning support more flexible with the owner facilities). It also ensures that user inputs to the dashboard can't impact critical systems, making it independent, as the framework can't write into the database. In fact, it is segregated in a way to rely only on database reads.
The API runs models that are trained offline, to keep sure that active models are reliable and have been tested before being deployed. Future development will add continual learning to the predictive models. In addition to that, a database flag notifies the framework of anomalous sensor data. Together, these measures contribute to making PREDICTiCS fault-proof and check all the 7 pillar principles.
Two kinds of models are used by the prediction service, a physics-driven one, that makes use of numerical simulations to profile the ship, and a data-driven one, that aggregates data from the ship's operation database.

[1] **RE**presentational **S**tate **T**ransfer **A**pplication **P**rogramming **I**nterface is a set of conventions and protocols for building and interacting with web services using standard HTTP methods to read, create, update or delete data.
[2] **U**ser **I**nterface, the interface where the interaction between operators and machines occurs.

4. Leveraging physics-driven and data-driven hybridation to build more robust predictive models

Both physics-driven and data-driven approaches have their limitations:

- physics-driven models are as good as the numerical-simulation models. Floating bodies simulation is known to be difficult[2], and we need to make a tradeoff between accuracy and computational costs. To get a wider coverage of the possible conditions domain, we have to reduce the accuracy of the simulations to be able to run more experiments.
- On the other hand, data-driven models are only as good as the data they were trained with. It is therefore needed to filter out noisy data, which should be handled by the data collecting component. Another issue raised by this reliance on quality data is that marine operations are biased, as planning tends to be conservative as to minimise costs and risks. This leads to highly imbalanced datasets, where worse operating conditions are under-represented, if they're represented at all: our data distribution is sparse and heterogeneous.

Because of the distinct characteristics of both the physical and data-based models, one cannot simply replace one with the other, or take the mean of their predictions. If the input sample is from a location in the data domain where historical data is missing, the data-driven model cannot be trusted, as neural networks are known to exhibit chaotic behaviour at training distribution boundaries. On the other hand, if the sample is from a densely populated location in the data domain, the neural network is bound to be more accurate than the simulation-based model.

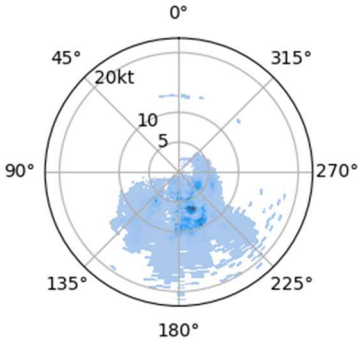

Figure 3 - Example of a biased apparent wind distribution

To account for this bias, a memory cell is introduced in the data-driven model. The distribution of samples used to train the neural network is tracked by it and can be used to provide a confidence level for prediction in a region of the data domain. This confidence level is then used to mix between the physics-based and data-based predictions.

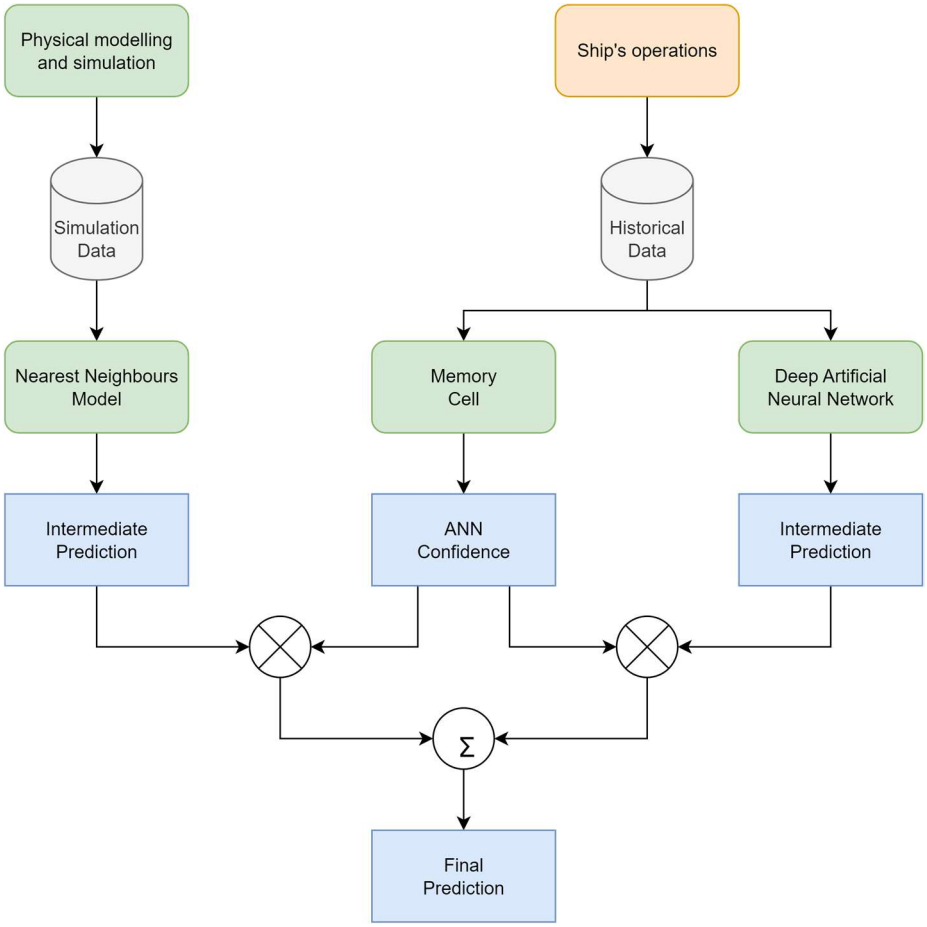

Figure 4 - Diagram of the hybrid model

- Nearest Neighbours Model: An algorithm that associates a value to a sample given the values of known samples close to it.
- ANN (Artificial Neural Network): A non-linear statistical prediction model which can learn complex patterns from data thanks to its hierarchical structure.
- Intermediate Predictions: Predictions from single components of the model (here the nearest neighbours and ANN components).
- Confidence: A score ranging from 0 to 1. It is used to evaluate how much the ANN prediction can be trusted.

4.1. Physics-driven prediction

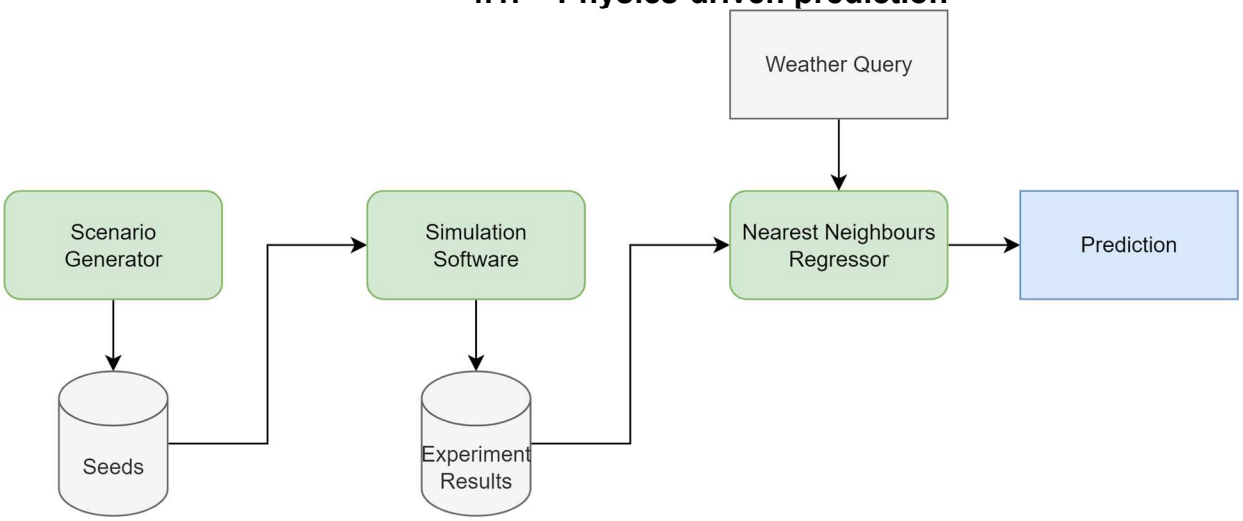

Figure 5 - Diagram of the physics-driven model trained from numerical simulation data

4.1.1. Designing simulation plans

Fully coupled dynamical simulations are used to generate data. Those simulations use the exact same control software that's used for operation, and test its ability to keep a position for 30 seconds per experiment. Hydrodynamics and aerodynamics simulations are handled by FRyDoM based software[2].
To achieve uniform coverage of possible weather conditions while minimising the amount of simulations necessary to have a decent knowledge and allowing for incremental enhancement (more simulations can be run and this new data can be added to the available pool without redundancy), random sampling methods are employed to generate seeds.
Using random sampling offers a strategic approach, ensuring that we capture a comprehensive snapshot of potential conditions. It minimises the risk of missing rare but significant events, enhances the representativeness of the dataset and prevents unnecessary duplication, ensuring the comprehensiveness and optimization of our simulations.
A weather state is described by a seed, which includes its wind and current components, with each component being defined by an angle/speed pair. Because they are defined in the polar domain, classical "grid-like" sampling methods would bias the distribution of seeds toward low speed, as demonstrated in figure 6.

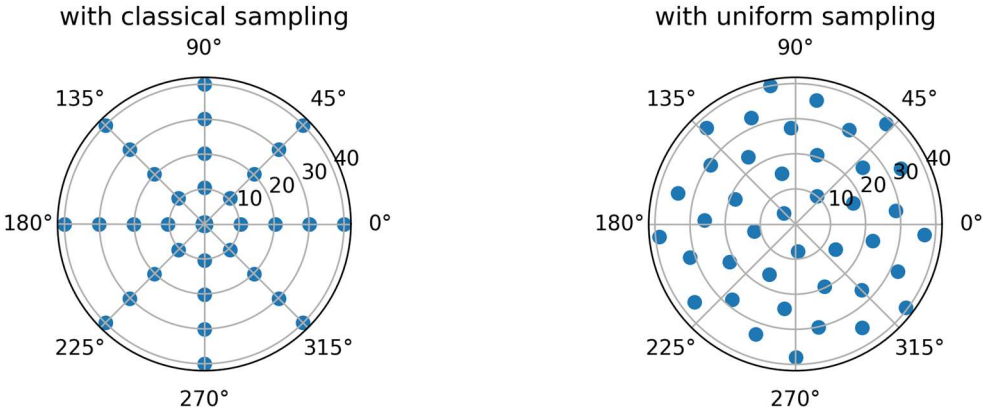

Figure 6 - Diagram illustrating the difference in distribution on a disc between two sampling methods.

To achieve a more uniform distribution of seeds, kernels are generated using the sunflower algorithm[6] as shown in figure 6. Once these kernels are generated, they are used as roots for the generation of random seeds distributed around them, as demonstrated in figure 7.

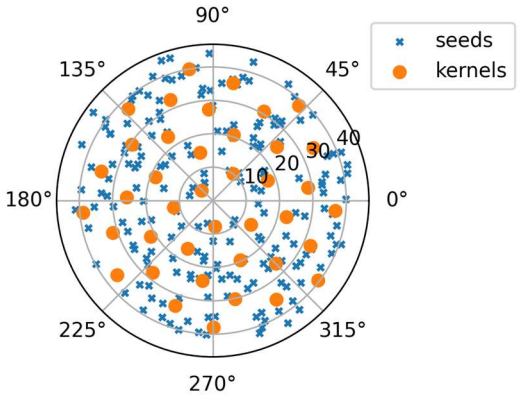

Figure 7 - Representation of the randomised seed generation procedure

4.1.2. Exploiting experiment results

Log data from the simulated ship's controller is output by simulations in the form of time series[3] with a 10 Hz sample rate. Each of these time series is then reduced to a single value, an error metric. By doing so, we reduce the memory footprint of the simulation data used for prediction from 25+Mb to <1 Kb per experiment, which represents a 99.996% space saving ratio.

Because a certain level of confidence is required for marine operations, and underestimating potential errors carries a high cost, the 90th percentile (see figure 8) of the distribution of measured absolute error is used as a metric. Then, an error upper bound can be associated with a seed's parameter, which can then be used to build the physics-based prediction model.

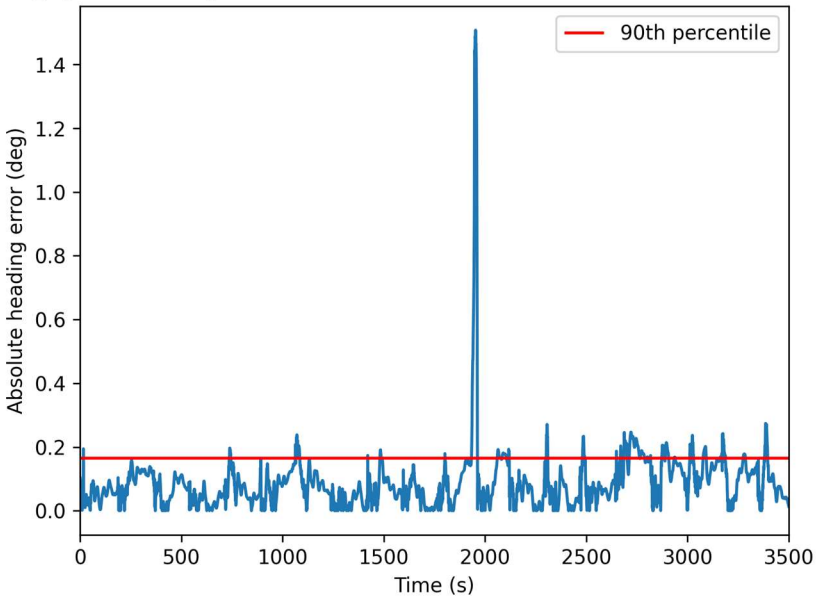

Figure 8 - 90th percentile of heading error.

[3]Structured sequence of samples, consisting of successive measurements made over a time interval.

To accomplish this, a tree data structure is used to store the experiment results, and nearest-neighbours queries are executed on it for prediction purposes. This allows for quick prediction thanks to the O(log N) complexity of nearest-neighbour search on trees. However, due to this approach, there is a limitation to the dimensionality of the data, as high-dimensional data tends to suffer from the curse of dimensionality, which makes distance metrics less and less reliable.

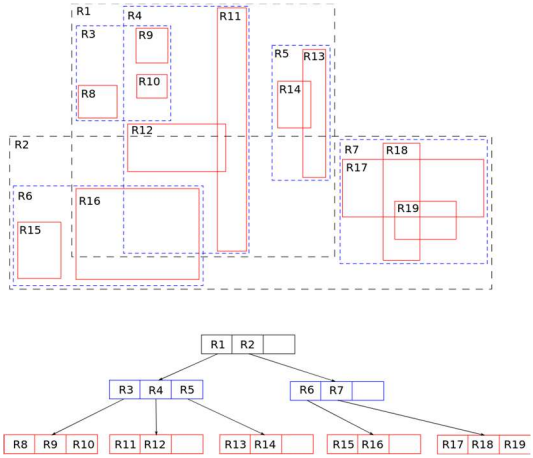

Figure 9 - Example of a tree data structure used to store two dimensional data. Source: wikimedia

4.1.3. Data Compression

Because the models can be incrementally improved by adding more experiment results to the tree, it means that their memory footprint can grow as well. To mitigate that, and keep the predictions accurate while reducing redundancies in data, a pruning algorithm (an algorithm that reduces the size of decision trees by removing sections of the tree that are redundant) is used to aggregate similar experiments: if similar seeds are associated with a similar error, they are then aggregated into a single node in the model's tree.

4.2. Data-Driven Prediction

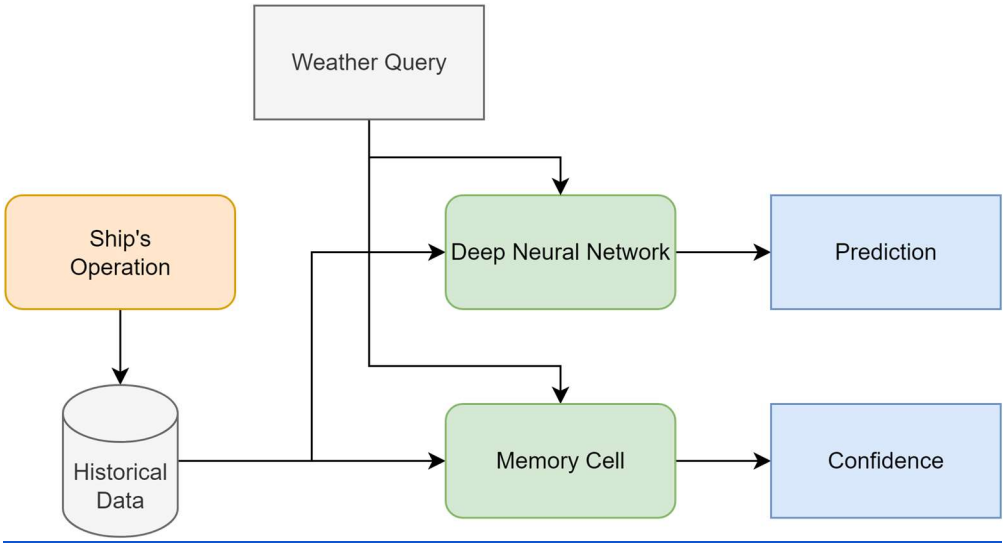

Figure 10 - Diagram of the data-based model trained with historical data

4.2.1. Data collection

Data is collected from the ship's operation database, extracting weather state and error metrics from 15 minute intervals, where the control mode was set. This sample duration is picked to have a statistically significant weather state. This data is then added to a dataset which is used to train a deep neural network. This training is done *offline*, which means that the model is trained from the whole dataset and then frozen before being deployed.

4.2.2. Memorization

To keep track of which conditions have been observed, which is necessary if we want to be able to tell how much the prediction can be trusted, a memory cell is added to the model.
This memory cell is an online density-estimation model that works by processing observations one by one.
Under the hood is a tree data-structure that holds points in 3D sphere, each point associated with a weather state, as follows:

$$\begin{aligned}
\rho &= \sqrt{\text{speed}_{current}^2 + \text{speed}_{wind}^2}; \\
x &= \rho \times sin(\varphi_{wind}) \times cos(\varphi_{current}); \\
y &= \rho \times sin(\varphi_{wind}) \times sin(\varphi_{current}); \\
z &= \rho \times cos(\varphi_{wind});
\end{aligned}$$

This data structure keeps a count of the number of occurrences seen in a neighbourhood, which can then be used to measure the local density, which provides the confidence score α:

$$\alpha(x) = \frac{1}{max(d)} \sum_{k \in V(x)} d_k \times exp(-||x-k||)^{-1}$$

This confidence score is then used as the mixing coefficient to get the hybrid prediction:

$$f(x) = f_P(x) \times (1 - \alpha(x)) + f_D(x) \times \alpha(x)$$

With f_P the physics-based prediction, and f_D the data-based prediction.

5. System Architecture & Integration

5.1. General System Overview

In 2017, D-ICE Engineering introduced a cutting-edge, all-inclusive navigation system known as OCEANiCS. This system is underpinned by a robust in-house software architecture seamlessly integrated with robust and high-quality marine approved hardware (DNV-GL 2.4). OCEANiCS is designed with a high degree of customization, providing a versatile array of functionalities, including:

1. **ECDIS** (Electronic Chart Display and Information System) Enabling precise and up-to-date electronic navigation charts for safe and efficient sea voyages.

2. **Autopilot & Track Control** Offering automated vessel steering and course tracking capabilities to enhance navigational accuracy and efficiency.

3. **Conning / Docking** Facilitating vessel manoeuvring, especially during docking and close-quarters navigation, with intuitive control interfaces.

4. **Dynamic Positioning** Powered by advanced nonlinear and robust control theory for better accuracy and lowered consumption

5. **Weather Forecast Analyses & Weather Routing** Providing advanced weather analysis and route optimization tools for safer and more efficient sea routes.

6. **Situational Awareness** Offering comprehensive data and displays to enhance a crew's understanding of their vessel's surroundings.

Beyond serving as a basic navigational tool, OCEANiCS emerges as a holistic maritime solution. Its adaptable and scalable design positions it for seamless integration with future features such as collision avoidance and automated docking.
The architecture of the system is organised into three key components:

1. **Control Panels with Human-Machine Interfaces (HMIs)**: These interfaces serve as the user-friendly control hub, providing accessible navigation and system management tools.

2. **Control Cabinets**: Located usually in Electronic Room, it houses the core control software, ensuring smooth system operation and functionality.

3. **Interface Cabinet**: Positioned usually near the engine room, this component connects with the ship's mechanical systems, facilitating real-time communication and coordination with onboard mechanisms.

OCEANiCS represents a state-of-the-art navigation solution that not only meets the demands of modern maritime operations but also paves the way for future advancements and seamless integration of emerging technologies.

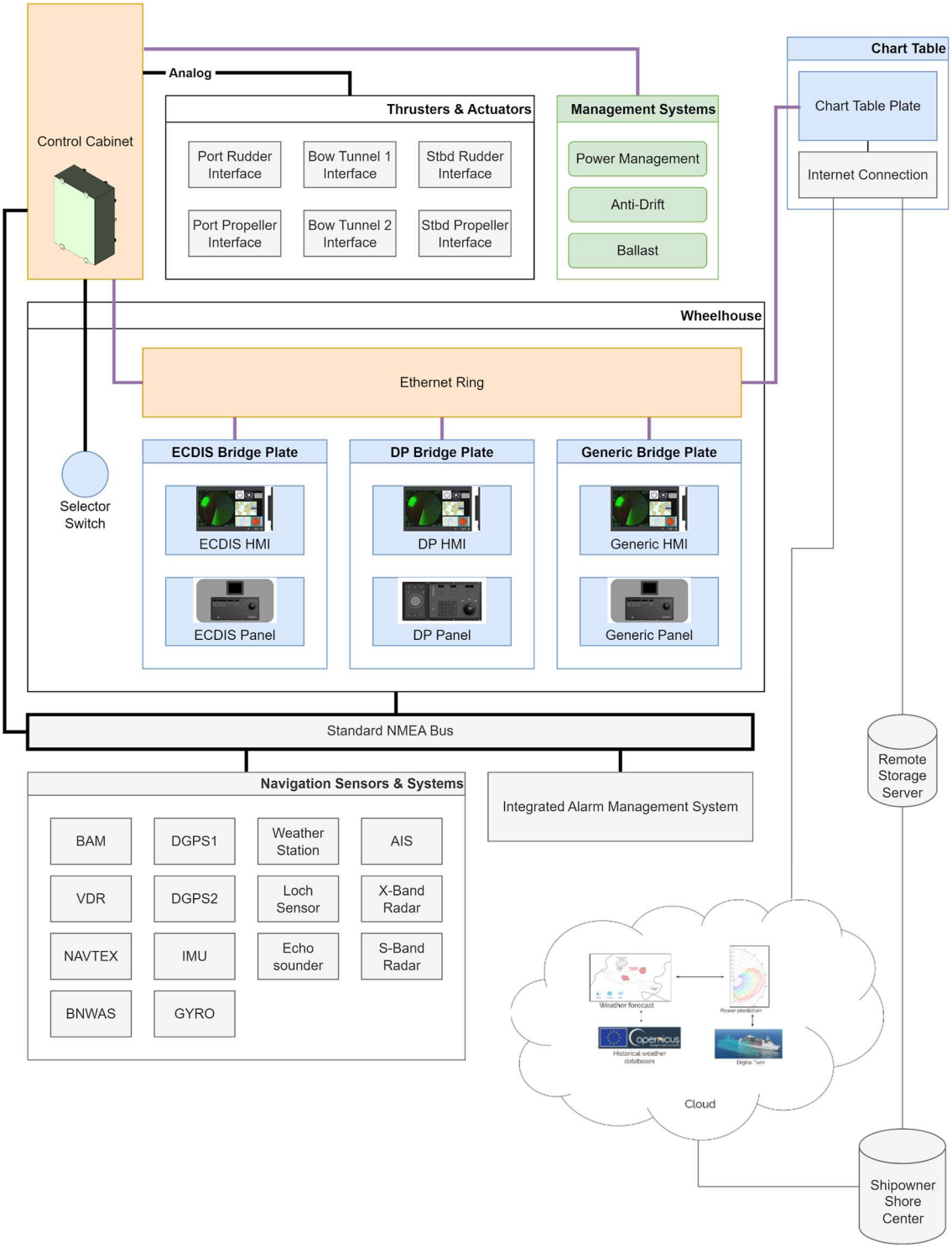

Figure 11 - Diagram of the OCEANiCS System Architecture

The approach we employ in OCEANiCS is firmly grounded in the principle of data collection mutualization and the application of edge computing principles. This strategic approach brings about a significant reduction in system complexity while concurrently advancing the sophistication of our

software. This transformative paradigm shift is made possible through the utilisation of our innovative software solutions and the expertise cultivated in-house.

Our navigational system integrates modern software engineering methodologies tailored for scientific applications, with key features such as :

- Adaptive Control Framework: At its core, OCEANiCS uses a universally applicable control framework. Crafted in modern C++ (C++ 20 standard) and cross platform by the use of CMake compilation toolchain.
- HMI Framework: OCEANiCS incorporates a Human-Machine Interface (HMI) framework built with C++/Qt. This framework is designed to automatically adjust its configuration, such as the count or positioning of actuators and sensors, in response to real-time data from the low-level controls.

Drawing a comparative analysis between a traditional dynamic positioning (DP) system and our system, our implementation drastically reduces computational time. This efficiency stems from our centralised architecture which utilises a single plate for processing. Consequently, everything is centralised and efficiently used, leading to a reduction in both cost and complexity. Thanks to this centralization, adding new components to the system is simpler: to access data, it isn't needed to multiply low-level communication channels.
However, every coin has two sides. With our approach, while there is simplicity and cost-efficiency, there is an increased risk of system failure. For instance, if the disk is overwhelmed with data, this would make the components reliant on that data unusable. In anticipation of inevitable anomalies, several mitigation strategies are incorporated. Additional testing & verification are made, alarms on disk overwhelm, data duplication and more.
The spirit behind our approach is balancing efficiency with functionality while being acutely aware of the potential risks. The advantages lie in cost-efficiency, streamlined operations, and rapid computational times. The disadvantages pivot around potential system failures due to an overload of data. However, by incorporating preemptive strategies, we strive to harness the efficiency of our system and keep the challenges in check.

5.2. Decision Support System Integration

5.2.1. Practical Integration Perspective

From a practical maritime perspective, the decision support system operates on a computer connected to the main DP system.
This specialised setup primarily focuses on functionalities like weather routing, performance analysis, and therefore forecasting via PREDICTiCS. All of these functions are consolidated on a single terminal we refer to as the Chart Table System. While applications on the Chart Table System can access data of the main component, they are intentionally restricted from writing data. Moreover, it's the only system connected to the internet, enabling the sharing of analyses and the reception of data essential for weather forecasting and routing. It is important to note that only specific limited internet connections are available to cope with cybersecurity issues.

In our commitment to maintaining the highest data quality for these applications, we have implemented a flagging mechanism. This system actively identifies and flags inconsistent or anomalous data from our sensors, ensuring that the Chart Table applications receive the most accurate and reliable data. Any data flagged as inconsistent is excluded from processing and analysis. This refinement underscores our dedication to precision and robust decision-making.

The proposed system accommodates weather routing, data analytics and performance analysis, among other features. It seamlessly communicates with the rest of our system using Ethernet protocols, serving as the central hub for decision-making on board. Besides, on the same system, the user has the possibility to open the Analytics Application, devoted to analyse recorded time series data. This allows the user to consolidate the decision-making process.

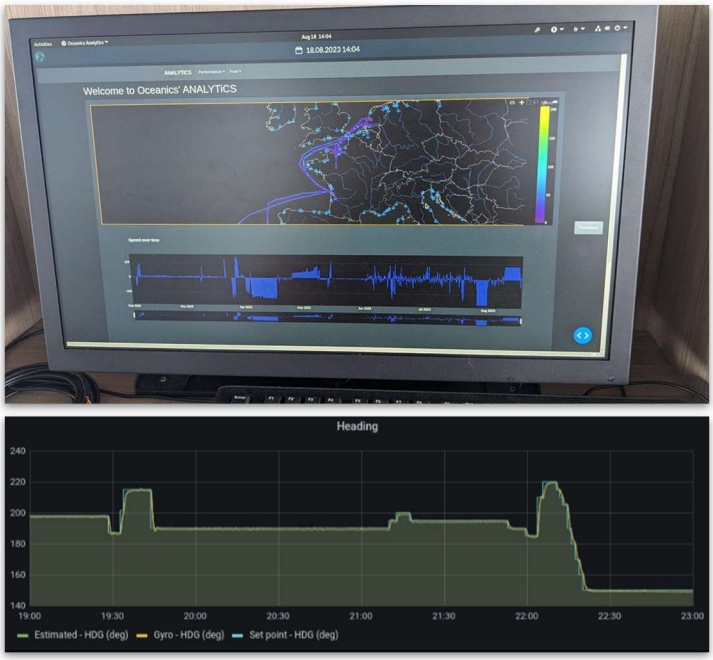

Figure 13 - Example of Time Series Analysis

Figure 14 - Crew checking OCEANiCS Weather & Routing application for operational planning on the Chart Table on Canopée Vessel

5.2.2. Key benefits of PREDICTiCS integration within OCEANiCS

The integration of PREDICTiCS into the OCEANiCS ecosystem promises a range of benefits :

- **Data Fusion**: Through its model and data focused methods, PREDICTiCS taps into live OCEANiCS sensor data. This collaboration guarantees that the predicted data is both current and precise.
- **Enhanced Decision Support**: By using the OCEANiCS Autopilot Track Control System, PREDICTiCS can offer predictive suggestions based on theoretical models and empirical data. For example in the case of a sensor or actuator failure, PREDICTiCS can provide an alternate action plan to maintain the operational consistency.
- **Adaptive Capabilities**: Considering OCEANiCS alerts the system for varying environmental conditions. PREDICTiCS can adjust its prediction models to take into account these dynamic changes. This ensures that its decision support remains relevant and prompt.
- **Dashboard Integration**: PREDICTiCS dashboard can be integrated smoothly into the OCEANiCS ecosystem and HMI, offering the operators a unified platform from which they can access all essential functionalities of a navigation system, from dynamic positioning to predictive analyses.
- **Evolution-Ready**: With OCEANiCS having the potential for further functional enhancements, PREDICTiCS stands ready to adapt and enhance its capabilities accordingly. This guarantees that the decision support system will advance as the maritime domain transforms.

6. Simulation Application Case

6.1. Case presentation

The first OCEANiCS DP Module has been installed on the Castor 02, a ship operated by Foselev Marine and based in La Seyne Sur Mer near Toulon. Insights of the DP control performances have been presented in the paper [8].

Figure 15 - Castor 02, the oldest offshore operation vessel currently registered under the French flag[4]. Source: marine marchande

At this stage of the development of PREDICTiCS, no full scale data from actual Castor 02 operations have been yet collected. However, to effectively develop and showcase the capabilities of this tool, the profile used to construct the simulation dataset has been voluntarily biased.
Subsequently, simulations were run a second time, employing this new virtual ship profile. The data generated from these simulations was then utilised in lieu of empirical data.

In total, 768 samples were generated for the simulation dataset, alongside an additional 768 samples for the simulated empirical dataset. Both datasets were employed for training the models, as detailed in Section 3. Subsequently, these models were deployed to an API instance, functioning as a backend for the interface showcased in the following figures.

6.2. Dashboard Panels

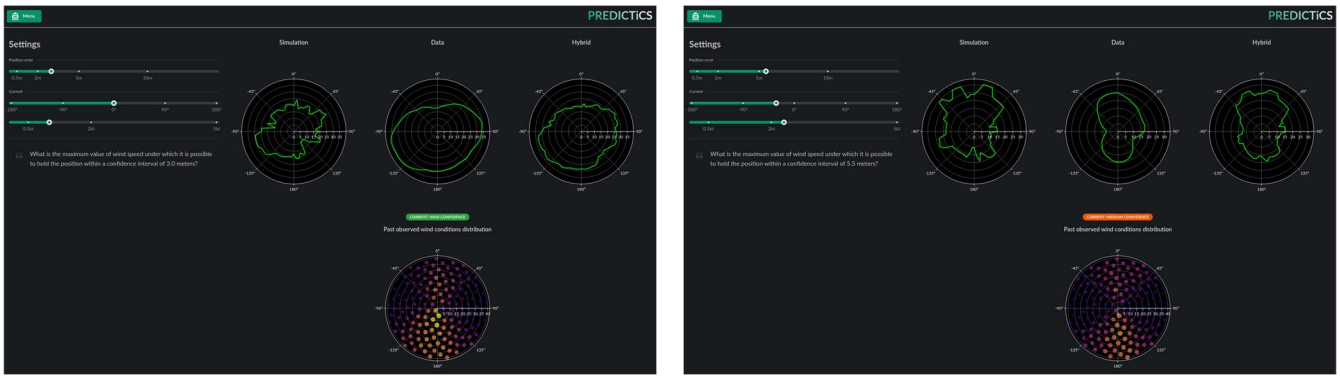

Figure 16 - Screenshots from the PREDICTiCS dashboard demonstrating predictions for different input current conditions and target position error.

The interface is divided in three different panels:

6.2.1. User inputs panel

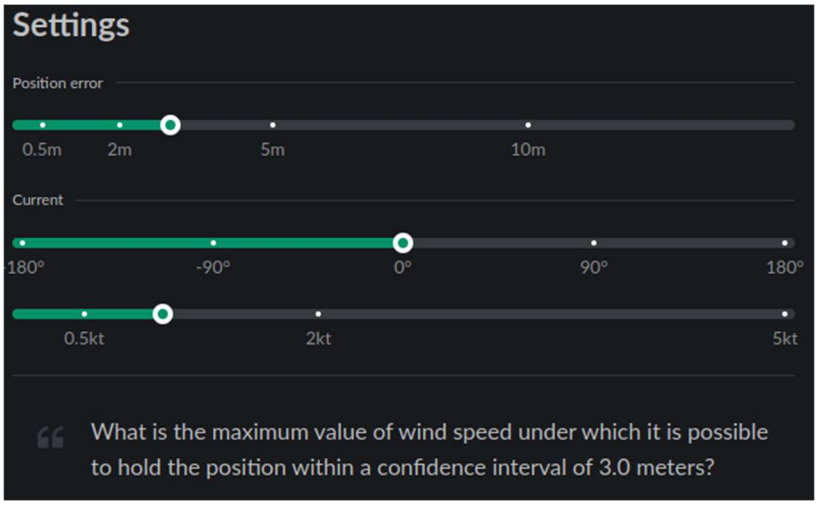

Figure 16 - Settings panel.

The user inputs panel allows the user to select the current conditions and what is the maximal acceptable position error. A paragraph explaining what the plots mean is displayed under the sliders.

6.2.2. Predictions panel

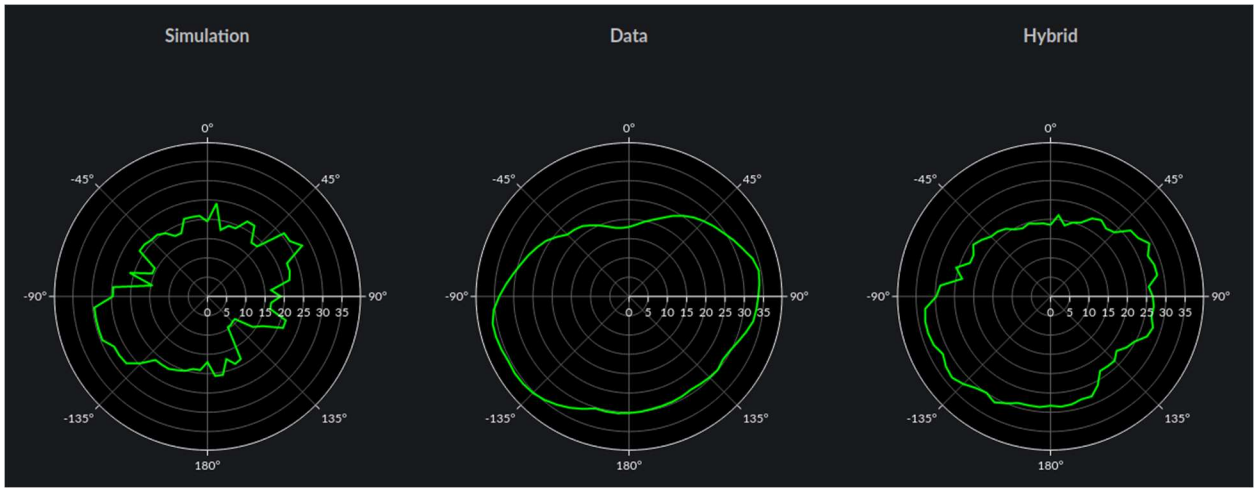

Figure 17 - Predictions panel.

This panel shows the prediction made based on the inputs given by the user.

6.2.3. Memory cell panel

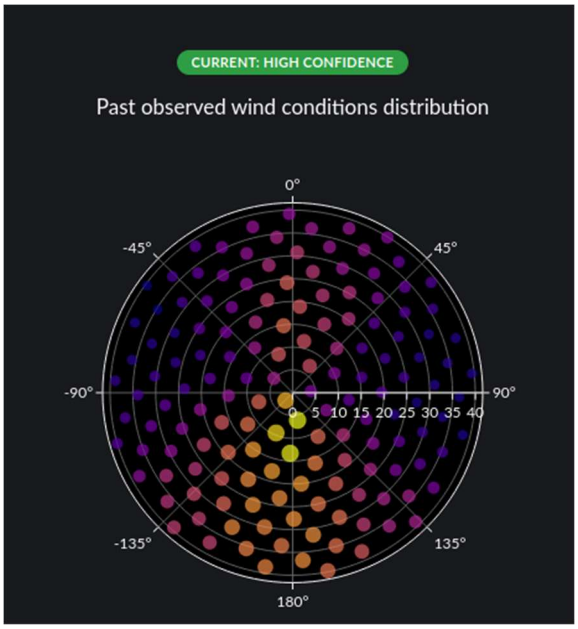

Figure 18 - Memory cell panel

Because the operator needs to know if the data-based predictions can be trusted, a component displaying the state of the memory cell is shown under the predictions panel. By providing a coloured quick-to-read bullet (here green, on top), it provides a swift insight, which can be improved by looking at the polar map showing the distribution of the past observations data (on the bottom).

7. Future developments and perspectives

This proposed framework for operation planification support is part of the broader vision developed at D-ICE Engineering. We want marine operation teams to have robust systems to help them carry out their missions while reducing the environmental footprint of the industry.
PREDICTiCS is a demonstration of this philosophy, which revolves around the following:

- high-fidelity fully coupled dynamic numerical simulation as a basis for performance prediction
- fully integrated operational system, from DP to performance evaluation to operation planning, with advanced and robust control at the cores
- data exploitation to enhance the decision support capability of the system

Now that this framework has been laid, we can envision different routes this project can explore to make it into a more efficient time and cost saver.

7.1. Simulation Core Improvements

Enhancing the initial simulation core, often referred to as the digital twin, is of paramount importance as it serves as the bedrock upon which the entire system is built. Elevating the precision of simulations directly correlates with improved decision-making capabilities, fostering a more seamless collaboration between users and PREDICTiCS.

This pursuit of refinement remains an ongoing and dynamic realm of research. Within D-ICE, multiple concurrent research initiatives are dedicated to advancing the fidelity of simulations in Dynamic Positioning (DP) Operations. For instance, the VIMFLO project, spearheaded by Technip Energies, is exclusively dedicated to pioneering an innovative asset tailored for the Operations and Maintenance (O&M) of Floating Offshore Wind Farms. This project exemplifies our commitment to pushing the boundaries of simulation accuracy and effectiveness in real-world applications.

Figure 18 - Artist view of VIMFLO Project

7.2. Live Monitoring

The efficacy of a support system hinges on its utilisation, and such utilisation is contingent upon trust. Presently, we are in the process of designing additional features and User Interfaces within the dashboard, affording users the capability to compare system-generated predictions with actual measurements. This feature empowers users to adjust their decision-making based on these comparisons. For instance, they can adapt to the predictions by discerning if the models exhibit a consistently conservative tendency or if performance begins to exhibit signs of degradation. This functionality aims to enhance the system's usability and engender trust among its users.

7.3. Modularization

The predictive model hybridization presented in this paper is raw. Because of the offline training strategy, the data-based model can be negatively affected by domain shift, an issue which is bound to happen given the lifecycle of operational vessels (bio-fouling, hardware degradation, etc.), that can't be corrected by the physics-based component, unless additional work is carried out to enhance the numerical models.
A solution to this problem could be to modularize the structure of the hybrid model even more, adding continual online learning[5] to the framework. This could allow the system to have predictive components ingesting data in real-time, without requiring the model to be retrained and redeployed every time new data is available.

7.4. Additional Parameters for the Prediction Module

The first design of the tool intends to use data that is easily accessible from any type of dynamically-positioned ship. So far, the model therefore relies only on data collected by the control core, that is, data measured by the sensors, which limits the model to only use for predictions of information that are measurable by those sensors. This leaves out relevant data, such as wave height, period or direction which is obviously a major parameter when designing marine operations. But, because of the centralised architecture of the system, data that is known a-posteriori, such as weather data from the system's weather component can be added to the pool of available data.

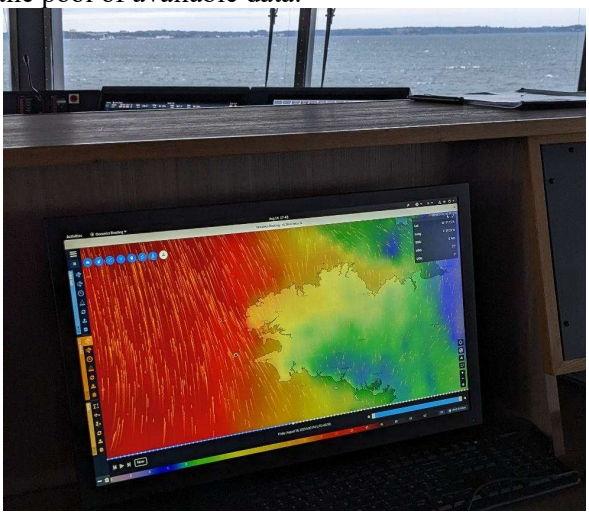

Figure 19 - Weather Forecasts Visualisation on the Chart Table System on the Canopée Ship

Moreover, additional R&D works will focus on the integration of additional parameters such as tuning of the DP System (control or estimator) or even the quality of sensors which has obviously an impact on the operations.
This will be a constant trade off between accuracy/exhaustivity versus the explosion of calculation time and complexity (resulting actually in infeasibility due to lack of computing memory, storage or processing power).

7.5. Extension to other applications and mutualisation

In 2022, OCEANiCS system was installed on the Canopée vessel, demonstrating the versatility of the solution. Canopée, a 121-metre cargo ship launched in 2022, is built to transports the Ariane 6 rocket from Europe to Kourou, Guyana. Equipped with 4 wing sails produced by Ayro (Oceanwings), this

pioneering vessel is the first modern wind-powered cargo in the world. The global concept aims at cutting fuel consumption up to 30% without affecting commercial operations (especially in terms of speed).

Figure 20 - Canopée vessel

The vessel has been equipped with the OCEANiCS platform fitted with ANALYTiCS, an intuitive tool designed for marine operators to analyse recorded data and facilitate various operational analyses related to their activities like : fuel consumption monitoring, heading control performance and more.

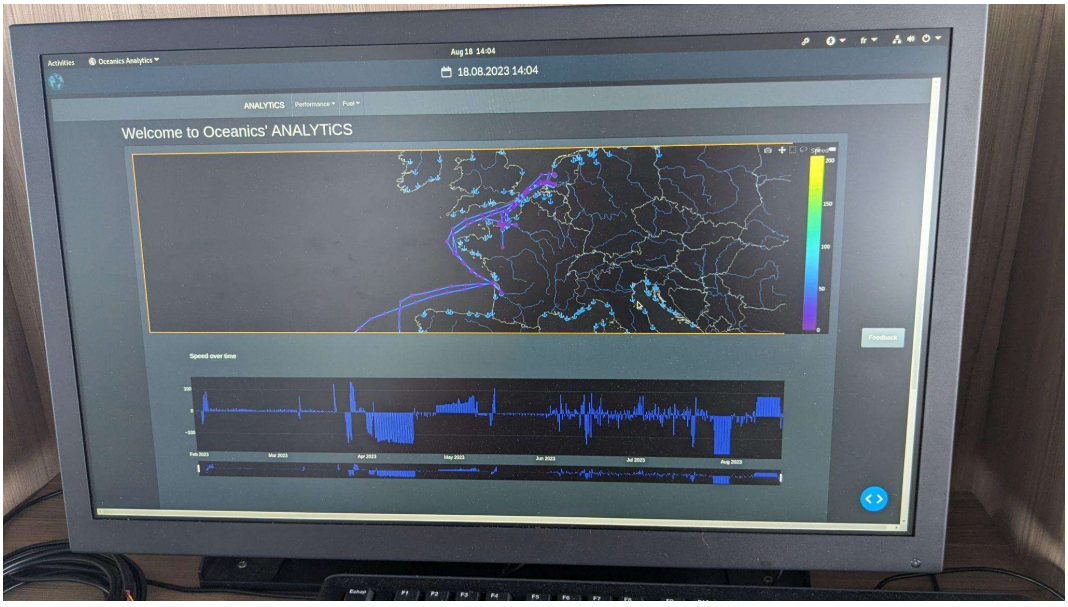

Figure 21 - Home page of ANALYTiCS showing Key Performance Indicators to the operator about the last vessel trips

With foundations set by ANALYTiCS on Canopée, this will result in enhancement of the user experience upon the integration of PREDICTiCS. This addition is expected to harmonise with the data processed by ANALYTICS. Notably, PREDICTiCS can repurpose this data for enriched analyses, such as taking into account the fuel consumption trends.

Today, this tool is used more and more by the operators on Canopée and not only because of the performance of the tool. The root cause lies in the performance of the core control systems. As discussed in the design philosophy, the users will trust digital tools only if the base of performances are sufficient.

Figure 22 - Example of heading control performances analyses on Canopée during the wings installation trials

8. Acknowledgements

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