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Via Kaizen

How to realize the most energy-efficient ship voyage in practice?

Executive Summary

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1. Introduction

The ongoing digitalization of society has reached the maritime sector, and an increasing amount of data is being made available digitally. All this data and information implies a lot of new possibilities but also many difficulties. The ability of humans to see patterns in large data sets and draw conclusions is constrained. Indeed, research has long pointed out that organizations and humans tend to choose what is good enough rather than what is optimal (Simon, 1957). Earlier research on shipping has shown that making large information sets available related to energy does not automatically lead to optimization of energy use, because interpretation and understanding of the data poses a lot of demands on the land organization and ship crew (Viktorelius and Lundh, 2019).

Artificial Intelligence (AI) and machine learning comes with great possibilities to revolutionize decision-making and planning in shipping. By training neural networks with large data sets, instead of having humans try to draw conclusions from them directly, for example about the factors that affects energy efficiency for a ship, optimal operational modes may be identified in real time. Such an aid would be of great use for planning ashore as well as decision-making onboard. Technical and mathematical research is rapidly growing. Access to reliable data sources and means of actual testing developed algorithms in practice require rare collaborations between shipowners, data measurement suppliers, which can be a barrier to this research. Also, studies using social science methods about the actual use of AI-based tools and technologies are scarcer for the same reason.

In this project actors from industry and academia have joined together to form a joint effort to:

i) Develop and implement a new AI-based, semi-autonomous planning and control system for increased energy efficiency in ship operations.
ii) Use gathered data to further develop and test new AI-based algorithms.
iii) Study the development and implementation of the system in actual operations.

The project integrates industry with technical and social sciences. It has brought together actors from academia and industry which have not previously collaborated. Yara Marine has led the project and has provided into the project their knowledge and experience of optimizing energy efficiency on vessels through the control system FuelOpt (see below). The company Molflow has contributed with their machine learning-based system Slipstream, that can produce digital twin performance models of a vessel. DNV have worked as subcontractors to Yara Marine to handle the actual project coordination.

The results of the project can be summarized as follows:

- The AI-based system has been successfully implemented onboard one ship on which the crew quickly understood both the value and the functionality of the system. On another ship, the operational pattern and pre-existing routines made the implementation more challenging and did not lead to systematic use of the system.
- A greater understanding of how to complement an AI-based system with the necessary training of the individuals using the systems has been gained.

Moreover, Yara Marine, Molflow and Chalmers, with DNV as subcontractors to Yara Marine, have successfully gained funding from the Vinnova call “AI in the service of climate” for a separate joint project to further develop ideas generated in this project. Halmstad University and University of Gothenburg have created a joint application to Trafikverket for funding for a PhD student to continue working in this area, in collaboration with DNV. Finally, Yara Marine has launched a commercial service called Route Pilot AI that builds upon the results of this project.

This system has already improved energy efficiency by controlling propeller and machine interaction. Interventions are planned at these shipping companies, where ship masters as well as the chartering departments are given a new tool to plan and execute voyages in an energy efficient manner. By analyzing existing work practices and user needs this new technology can be developed so that it supports actual processes and decisions with greatest impact on energy efficiency. In this way, we have completed the process so that the most energy efficient voyage can be realized in practice.

This report is divided as follows: Section 2 details the background to the project, from the perspective of each actor. Section 3 describes the project plan. Section 4 presents the results of the project. In Section 5 the results are discussed, and further research ideas are presented. Section 6 presents conclusions and the final section (number 7) is a reference list of the different scientific papers published within the project.

2. Background

The project has brought together actors from both industry and academia. Here, the background to the project from the different industry perspectives and from the different academic disciplines is given.

2.1. Participants in the project

Yara Marine Technologies (YMT) (previously Lean Marine) is a company that, among other things, develops and markets the products FuelOpt and Fleet Analytics as well as carries out R&D within the field of vessel optimization. Both of YMT's products have been used to create a steppingstone for the research and development within the project as they previously have been installed on the vessels that were used as trial cases in this project. Each technology is described in more detail in section 2.2.

Molflow is a consultancy company experienced in big data sets, decision support systems and remote measurements. Molflow have supported many remote sensing space born research project and developed strategies to handle large amount of data in efficient data pipelines to support processing of complex data. Since 2015 Molflow has been involved in route optimization at sea, through development of the product "Slipstream", described in section 2.4.

There are two research groups from academia participating in the project. From the social science side, Martin Viktorelius from Halmstad University and Simon Larsson from University of Gothenburg. Martin Viktorelius did his PhD at Chalmers on energy efficiency in ship operations, based on field research at Stena Line and Styrsöbolaget. At the start of this project, he was a Post doc at Linnéuniversitetet, and is now assistant professor at Halmstad University. Simon Larsson is a researcher with a background in social anthropology. Before joining this project, he has worked with Volvo on implementing AI in their factories. From the engineering side, professor Wengang Mao has participated with his research group. He has worked for many years on building new models for determining the performance of ships based on measured data.

Other than the project partners, two shipping companies have been providing case study vessels to test the developed system: UECC, a shipping company operating pure car carriers (PCCs), and Stenersen, a shipping company operating chemical tankers. The companies have been active in providing data to Chalmers and have been working together with the social science team to provide access to ships and crew. DNV has been working for Yara Marine as subcontractors to help coordinate the project.

2.2. Optimal voyage execution

The project is centered on enabling crew to execute voyages in the most energy efficient way, once an ETA has been set and a route been decided on. It is especially concerned with short sea shipping, where there are not that many different routes to take (cfr. trans-Atlantic voyages). The main technology utilized in the project is the system FuelOpt, to be explained below. However, the project results are not reliant on this specific technology; the results could be implemented with other solutions.

FuelOpt

FuelOpt is an onboard system that enables the vessel's crew to control the vessel based on setpoints for speed, fuel consumption or propulsion power, as seen in the figure below. FuelOpt regulates the propulsion machinery to always keep to the setpoints.

Much like a cruise control in a car brings stability and predictability to the speed and fuel consumption of the car, FuelOpt works on the same principle for a seagoing vessel. At sea, however, the parameters are much different than on the roads. A seagoing vessel is heavily influenced by external factors such as weather and currents which will create large variations in speed and fuel consumption unless carefully managed. Whereas a car is constrained by specific speed limits and traffic at each point of its trip, a seagoing vessel is instead more generally constrained by timetables or commercial parameters that govern which speed and consumption it should maintain. This means that a vessel will have a comparatively high degree of freedom in finding an optimum operational strategy.

Previous analyses by YMT have shown that this automated attention to the vessels operational parameters can save a vessel on average 3-4% of fuel consumed per year. An analysis carried out recently by the company NAPA showed even better savings: 17.9% improvement for a product tanker in the fleet of Stenersen, and 10.3% savings for a similar tanker in the fleet of Ektank.

FuelOpt presents itself as a tool to execute operational strategies. The traditional way of operating a vessel requires the crew to manually adjust the propulsion system as the weather

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or currents change. This can be done with different goals: either to have a constant speed through water or over ground (with varying fuel consumption), or to achieve a stable and controlled fuel consumption (with varying speed). FuelOpt assists with the latter goal by doing this automatically.

The above points are illustrated in Figure 1 below. Here, the two different strategies of sailing with fixed power or fixed speed over ground are displayed. A ship is simulated to sail on a route on the North Atlantic, with two different strategies – either fixed speed over ground, or by an optimum power (done by the system Slipstream, to be explained further below). On a constant propulsive power level, the speed varies as the ship encounters wind, waves and current. For a constant speed, the ship needs to increase or decrease power to maintain the speed. In this case, the fixed speed setting uses 17% more power.

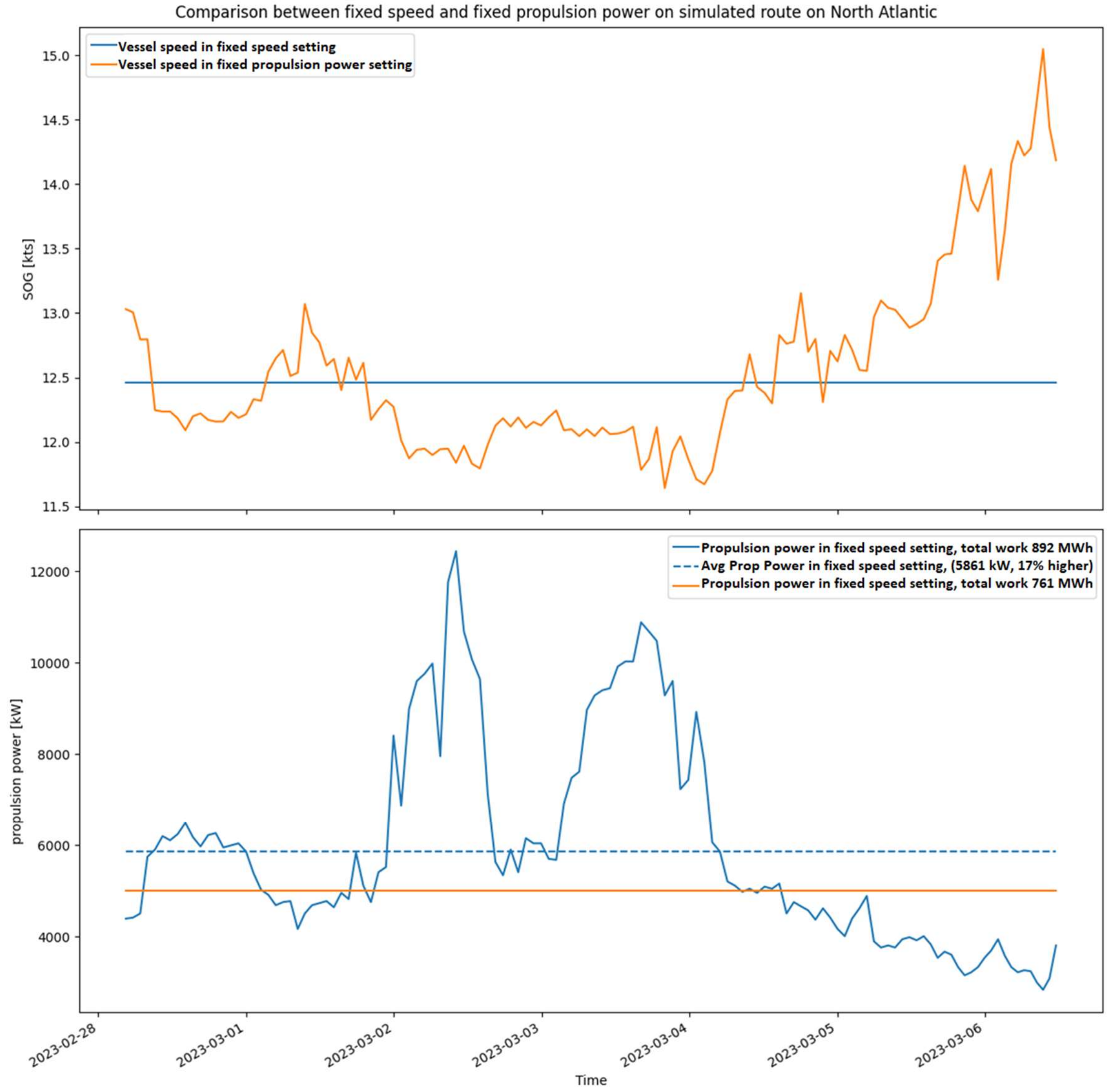

Figure 1 – Comparison between fixed speed and fixed propulsion power on a simulated route on North Atlantic.

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There are, however, at least two challenges to realize these savings:

1) The value of the setpoints to execute should be evaluated before the voyage is started. This means that a capacity to determine which is the optimal constant power is needed.
2) The vessel's crew needs to be encouraged and convinced to modify their operational routines. This means that they need to trust that sailing on this optimal power will still mean that they arrive on time.

Within the scope of this project, both these challenges have been investigated and addressed. Specifically, through working with data collected from the vessel for power estimations. Collecting data is a secondary but equally important function of FuelOpt. The system integrates with several data sources, logs high frequency performance data, and continuously transmits this data from the vessel to an "onshore" cloud database. This type of data has been used by all project members in their analyses as well as for building the machine learning models on which the project results are largely based. The functions of this system, called Fleet Analytics, is described below.

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Fleet Analytics
Fleet Analytics is a web-based tool for visualizing and augmenting the data that is collected and transmitted from the vessel. It contains several different functions that are all related to following up and analyzing a vessels operational performance as well as providing an interface for the crew to complement the automatically logged data with manually reported data. The tool enables full overview of a vessel's performance and is also the basis for creating essential reports on e.g., emissions and a vessels ability to operate according to its best operational practice. A snapshot is provided in **Error! Reference source not found.** below.

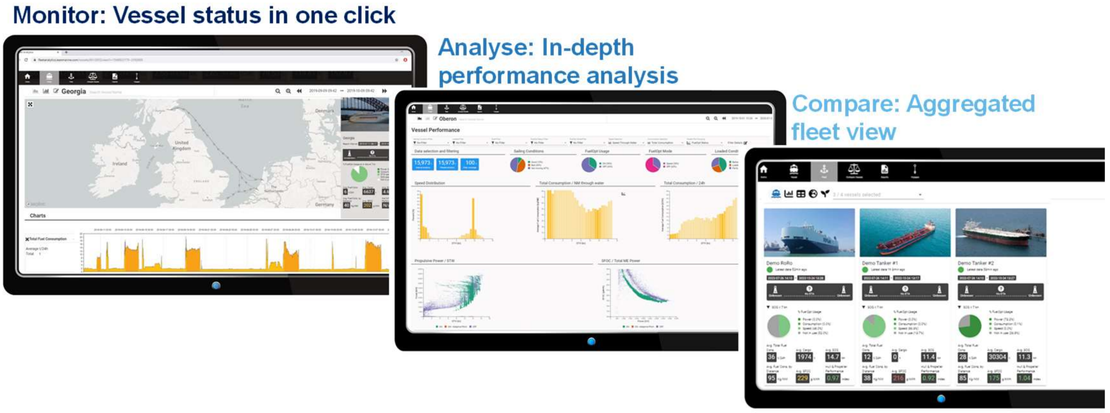

Figure 2 - Fleet analytics dashboards

In this project, Fleet Analytics has been used to share operational data on vessels between all project members. Operational data has been used to train the models developed by Molflow (see below) which were then used in the implemented system. The operational data has also been used by Chalmers to explore and develop new kinds of AI-based models.

The weakest link in any data collection and analysis platform is the quality and incompleteness of the data that is available from a vessel. Vessels will differ with regards to which data signals are available for automatic logging and it is common that certain key performance parameters are missing from the data set. Fleet Analytics' way to solve this is by enabling manual inputs to "fill in the gaps". This requires a good routine at the user side which sometimes can be a challenge to implement.

2.3. Bringing data to better use

The two technologies described above represents two important parts in the process aiming for realizing the most energy efficient route. FuelOpt represents a tool for executing instructions with high precision. Fleet Analytics makes data accessible that can be used to evaluate the results of the execution after it has been carried out.

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The third part of the process was identified leading up to this project, that has the potential to close the circle of continuous improvement. By using collected historical data a digital performance model of a vessel, a so-called “digital twin”, can be established. This can be used to predict the behavior of a vessel in upcoming voyages and bridge the gap between analysis and better execution. Technology would need to be developed, and put in the hands of the end user, that allows executable instructions to be optimized regularly and during voyages to handle changes in operational parameters.

To develop and trial such a tool has been of the goals of this project. Throughout the project, the YMT technologies already in place have acted as a platform on which to evaluate this new tool. It needs to be stressed that the results of the project are not reliant on these specific technologies. There are alternative solutions for sailing the vessel, and especially for collecting measured data.

2.4. Planning the most energy-efficient way to execute a voyage

The main planning tool used in this project is Slipstream, developed by Molflow. This system could be replaced by others with the same functionality. In fact, an important part of the work of Chalmers was to develop and test new AI-models. This technology is described below.

Slipstream
Slipstream is a decision support system to calculate the optimal execution of a given route with respect to sea conditions, developed prior to this project. It simulates and optimizes the outcome of the route before execution and during execution. Slipstream uses logged data from vessels to build a self-learning ship model, a digital twin, to simulate the given route with available weather forecasts. The unique error propagation from the digital twin combined with the inaccuracies from the weather forecasts provides a notification to the users of the system when they should rely on stable condition thought out the execution of the route or if they should expect large deviances from the predicted results. Slipstream also keeps track of the ship's performance over time. It can detect biofouling or other degradation issues.

The system was when the project started already a complete standalone system, with graphical interface for bridge users to optimize routes in a web interface. As such it could be used in combination with other systems beyond the setting explored in this project. A requirement to be able use the system is to provide vessel data to it (for model training). In this project the vessel data source is Fleet Analytics and optimizations run via backend request from Fleet Analytics.

The basic idea with the optimization of routes is a compromise between simplicity in execution and correctness. A fixed propulsion power over a route – made possible by for example a FuelOpt installation – leads to a fixed cost per hour and simple execution control. In reality, a less costly route execution might exist, at the cost of a far more complex execution model. For example, two different fixed-power settings could be more optimal, but more complex to execute.

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The incentive is to use as little energy as possible but still complete the route within a certain time. Let us assume a fictive ship with the calm water speed-power baseline depicted in Figure 3 below, exemplified with a simple polynomial function. Then assume a route in calm water with no currents, where the ship owner needs to deliver cargo within a certain time that requires a mean speed of 12 knots. In calm water with no currents the optimal solution is simple - go with 12 knots. But if environmental conditions are a bit unclear – perhaps there is potentially a strong current, or it seems difficult to assess the impact of the incoming weather – bridge crew can “buy” some margins by going faster in the first half of the route and then go slower the second half of the route. If the crew chooses to go 13 knots in the first half and 11 knots in the second half - the ship would use 1.7% more propulsion energy than going on a steady 12 knots during the whole route.

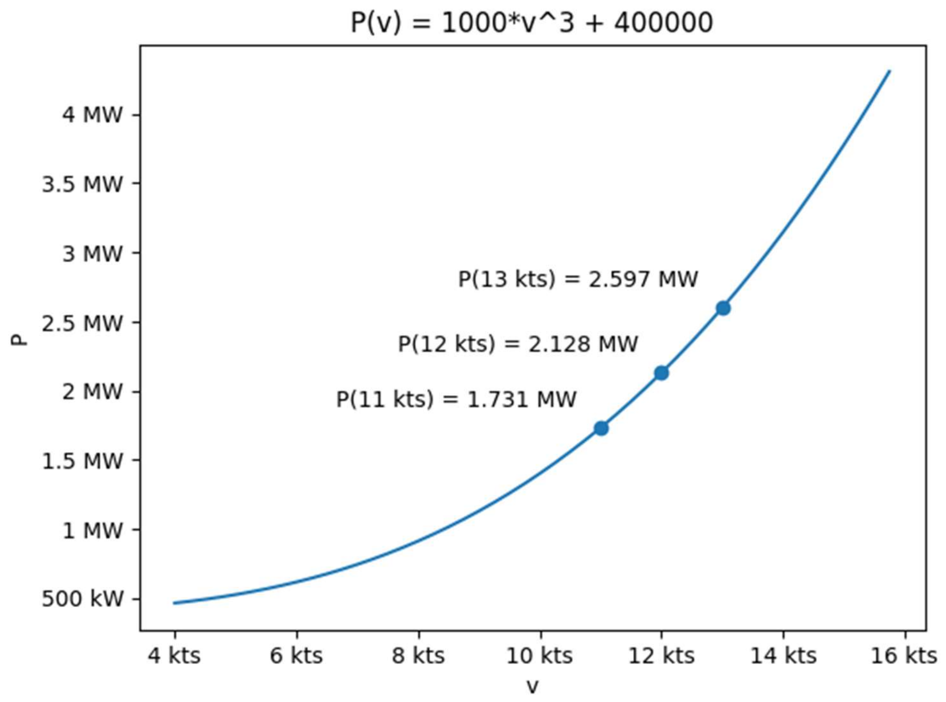

Figure 3 – A fictive calm water baseline based on a simple polynomial. Due to non-linearities in the baseline; going a step faster than necessary will always use more energy than going a step slower. E.g. The decided transport speed 12kts will need a propulsion power of 2.128MW. If you choose with 13 kts half the time and 11kts the mean propulsion power will be higher (2.164MW).

In a real-world example (with winds, waves and currents) slipstream has learnt how the ship performs in all conditions and can estimate the ships speed along the full route. In Figure 4 below, an actually executed route (blue) is compared with an optimized route with a fixed power setting.

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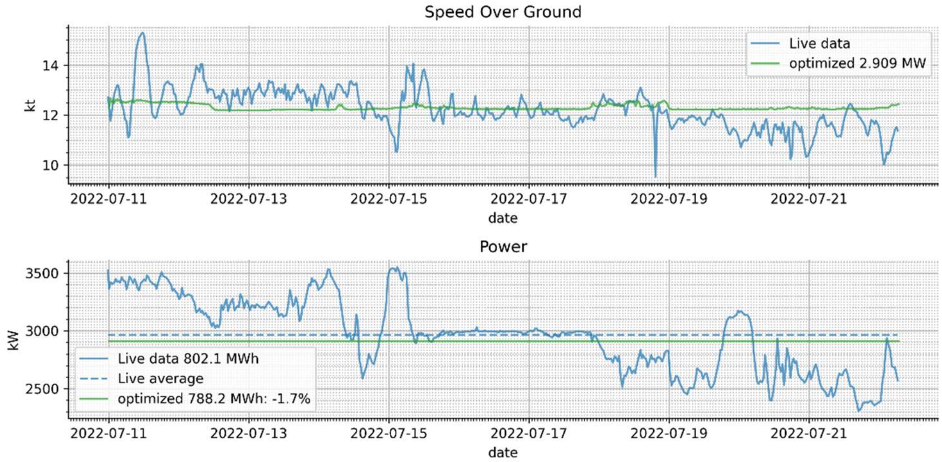

Figure 4 - Upper panel shows speed over ground. The lower panel shows propulsion power. Blue lines come from a ship, green lines are from an optimized run. The graph shows that the propulsion power is 1.7% lower for the same route.

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3. Project plan

On a high level, the project can be described as having three parallel workstreams with main responsible actors, as described in Figure 5 below.

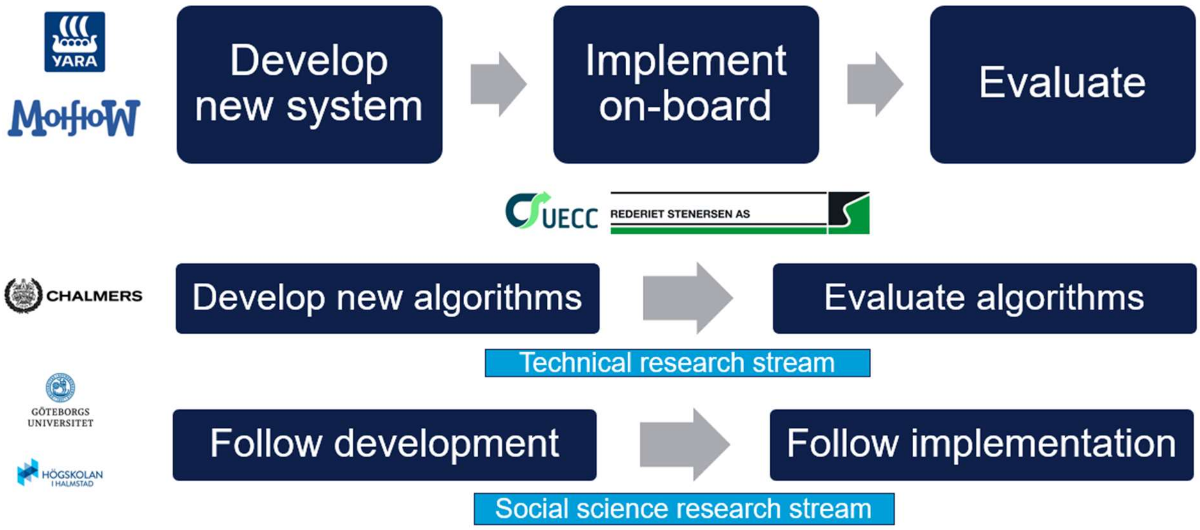

Figure 5 – The parallel workstreams of the development

In practice, in particular the evaluation was carried out jointly. The project team including all parties had re-occurring meetings every second week to catch-up on on-going work and identify any blockers hindering others from being able to do their work. In addition, workshops and longer sessions were scheduled as needed. As COVID restrictions were removed, both the workshops and re-occurring meetings also took place physically.

In this section, the overall project plan for the different actors in the project are presented: the development and implementation of the onboard system by Yara Marine and Molflow in section 3.1, the technical research by Chalmers in section 3.2, and the social science research by Halmstad University and University of Gothenburg in section 3.3.

3.1. Development and implementation (Yara Marine and Molflow)

YMT's primary purpose was to develop and implement the user interface part of a tool for optimizing voyages using deep learning performance models. The main users in the project were vessel crews (captains and officers). Therefore, a secondary purpose was to understand what above mentioned tool needed to provide in terms of user experience and functions in order to be adoptable by the user group.

Also, YMT was collecting data from the vessels throughout the project and has evaluated the degree to which the tool was used and primary results on the vessels' performance.

Molflow's purpose in the project is to deliver route optimization with ship models trained on logged data from Yara Marine Technology's system Fleet Analytics. As well as develop and maintain an API for YMT to use for optimizations we continue to develop the AI-model according to the project findings – this is done during WP3.

The work done by YMT can be separated into two categories.

1. Development of a web-based tool for accessing a vessel's performance model as developed by Molflow. The tool had to be able to let the user define an upcoming voyage (route and time) and present an optimized voyage instruction that the user (vessel crew) was able to execute in-voyage. This work has been carried out by YMT development team throughout the entire project period.
2. Implementation, user training, support and evaluation of the tool in the hands of the user. Two trial vessels and their crew were in focus in this phase. This work started about half-way into the project period and consisted of a number of training sessions, creating guides/manuals and following up on the user experience. Based on feedback from the users, some additional features could be prioritized in the development. New functionality could be launched and introduced to the crew of the vessels gradually with follow up on the experience and the impact on the usage of the tools.

3.1.1. Development

The development work involved several different resources within YMT such as domain experts within the field of onboard ship systems and operation, product management and a team of software developers.

User stories were early identified and written to reflect the different work flows that the tool had to support. This included the ability to import route files from nautical planning software and navigation stations onboard. To simplify the use of already reoccurring voyages, already imported route files had to be stored and organized in an archive. Another way to define a route is to re-use an historical voyage already sailed by the vessel. A route is in the tool a geometric object that can be referred to by a schedule. A schedule is defined as being a route scheduled in time and with reference to a vessel and its loading condition. In the schedule editor of the tool, the user can add the required information that needs to be provided in the request to the simulation model. This includes selection of a vessel out of the available fleet, and information regarding the loading condition for the voyage, defined by the vessel forward and aft draft.

When a planned schedule gets into the phase of active execution, the schedule supports simplified re-simulation where the actual position and time of the vessel will define the starting point of the simulation, without any manual editing of the schedule. The tool includes also

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different visualizations that present the result of the simulation to the user and recommended settings for the onboard optimization system that will execute the voyage accordingly.

Besides the user interface of the tool the work included design and development of the backend related to the communication in between the Fleet Analytics platform and the Slipstream system. The design of the interface was done and agreed upon in close cooperation between the Molflow and the YMT teams of developers. The frameworks used for requests and responses are based on standard file formats and protocols. The development and implementation were done in iterative steps and in close dialogue between the two parties.

3.1.2. Implementation

YMT's FuelOpt system was already onboard the vessels involved in the project. This technology was a central part in collecting data from the vessels. FuelOpt also provided a tool with which to execute the instructions that were calculated and optimized by the tool developed in the project. The implementation and support of the crews of the vessels involved was mainly carried out by the customer success support department of YMT.

Early in the project, during WP3 Molflow adapted Slipstream to read vessel data Fleet Analytics and enabled optimizations from Fleet Analytics, during the later parts of WP3, Molflow adjusted the ship model algorithms according to findings when iterating with project members and crew onboard.

3.2. Technical research (Chalmers)

3.2.1. Pure machine learning black box model

A ship's performance modelling can be carried out with different levels of complexity, such as theory-based (physical) models and data-driven models. The physical models were often developed for ship design purposes and contain large uncertainties for ship operation related measures. Driven by the shipping digitization, large amounts of ship energy consumption related data have been collected. Based on those data, shipping companies tend to use simple statistical methods for ship operation related measures, such as linear regression to predict performance trends for sail planning and ship hull cleaning, etc. The maritime community is keen to exploit more usage of their collected ship data

Sophisticated machine learning methods have been investigated to build data driven ship performance models with higher prediction accuracy. Often very low resolution of data such as noon reports is used for the ship speed-power performance modelling due to lack of ship data access. Those ship fuel performance models are mainly trained to monitor/estimate a ship's fuel/power consumption in terms of ship operational parameters, e.g., ship speed, engine RPM, draft, or shaft power. However, to apply data-driven ship models for energy efficiency measures in optimal ship operations, it is essential to model a ship's energy performance in terms of encountered metocean environments. And the capability and sensitivity of different machine learning techniques were not well discussed in the public community.

Slipstream, the system used in this project, relies mainly on machine learning techniques. So, from the academic perspective, it is very interesting to test alternatives. In this project, different supervised machine learning algorithms, i.e., XGBoost, artificial neural network, support vector regression, and statistic methods, such as linear regression, polynomial regression, generalized additive model are applied to establish data driven speed-power model for a case study chemical tanker and PCTC. The model describes the relationship between ship propulsion power and all possible influence parameters (input features) from full-scale measurement data. The considered input features belonging to the general ship operation (ship speed through water, draft, trim) and weather conditions (wave and wind).

A generic data pre-process framework is proposed and applied in this project, i.e., data synchronization, sea passage extraction, obvious outliers deletion, repeated values and drop-outs excluded, maneuvering conditions and spike values detection in the raw measurements.

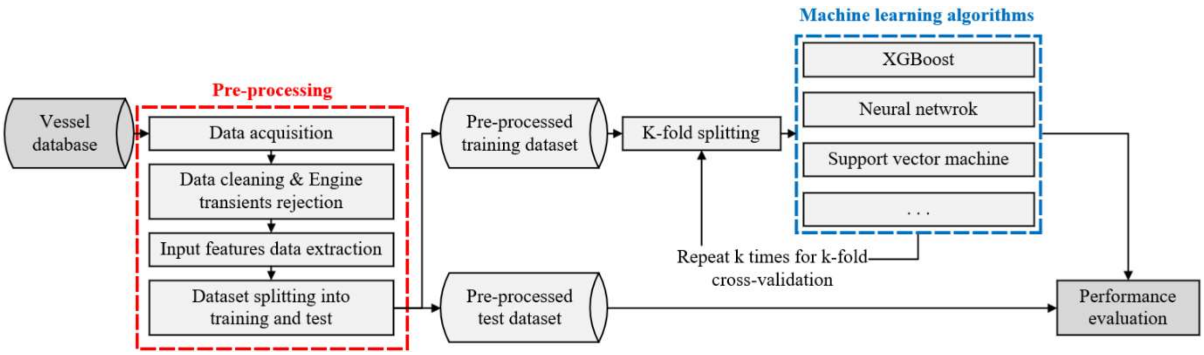

Figure 6 – Workflow to establish data-driven models for a ship's propulsion power using different machine learning algorithms.

The workflow of the machine learning modelling is presented in Figure 6. First, full-scale measurement data is processed and feature-selected in the data processing stage. Then the processed (clean) data is split into the training set and test set, and then standardized. The cross-validation is implemented to tune hyperparameters to decrease the generalization error, in the form of k-fold for the training set. It should be noted that several complete voyages are separated as validation set (not used for model training and test process), to evaluate the model for applications of future unseen navigation.

The results of model metrics and the training time of different models on test set are compared and listed in Table 1. The machine learning models have higher accuracy than the explicitly regressed models. For the chemical tanker with a much longer measurement period, the statistical methods give worse prediction than those for the PCTC, since they cannot capture the speed-power relationship in terms of large variation of other related parameters, such as wind, wave, heading, draft, etc. But the time required for the statistical approaches is very short. Especially for the linear regression and polynomial regression, the training time is less than 1 second. As for these three machine learning algorithms, although neural network and support vector regression have similar predictive capabilities to XGBoost, they require up to

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10 times of training time. Especially for the chemical tanker with a larger dataset, the training time difference is about 15 times. This is the advantage of the tree boosting system based XGBoost method. It has good performance with much higher prediction efficiency.

Table 1 – Accuracy measures of various machine learning data-driven models applied on the test set

Ship type	Algorithm	*MAE* [kW]	*RMSE* [kW]	R^2[-]	Time [s]
Chemical tanker	Linear regression	565.8	727.9	0.6775	< 1
	Polynomial regression	379.1	490.3	0.8537	< 1
	GAM	338.6	445.9	0.8789	5.3
	Neural network	57.9	89.6	0.9943	170.2
	Support vector regression	73.4	100.8	0.9938	176.6
	XGBoost	46.4	82.8	0.9958	11.7
PCTC	Linear regression	424.3	530.6	0.8415	< 1
	Polynomial regression	148.6	204.7	0.9764	< 1
	GAM	195.9	255.5	0.9632	1.2
	Neural network	84.0	120.2	0.9919	37
	Support vector regression	83.7	115.9	0.9924	12.9
	XGBoost	71.0	108.4	0.9934	3.3

For the validation on unseen sailing voyages, the XGBoost model has very good prediction results, where the artificial neural network and support vector regression models have much higher prediction errors and are not stable in the time series. Figure 7 presents one unseen voyage 2017-10-05 case study. The black markers represent the measurement data, and red markers for the prediction by the XGBoost model. For this case study voyage, the XGBoost method generates the best data-driven ship performance model, with only a maximum error of about 200 kW. The prediction errors of ANN and SVR models for this voyage are significant. The physical model can predict better propulsion power than the data-driven models developed by ANN, SVR and the regression methods, with a maximum error of around 1000 kW. The powers predicted by the physical model are constantly under the measured values during this voyage, while ANN, SVR, and the statistical methods always over-predict the powers.

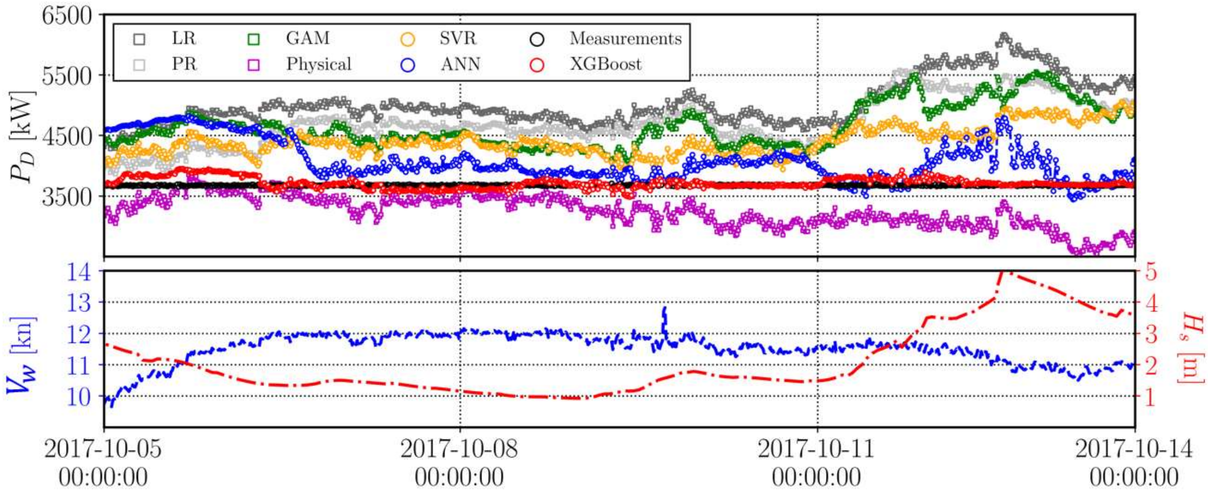

Figure 7 – Comparison of ship's propulsion power prediction by various models, as well as ship speed V_w, encountered significant wave height H_s along the case study voyage 2017-10-05.

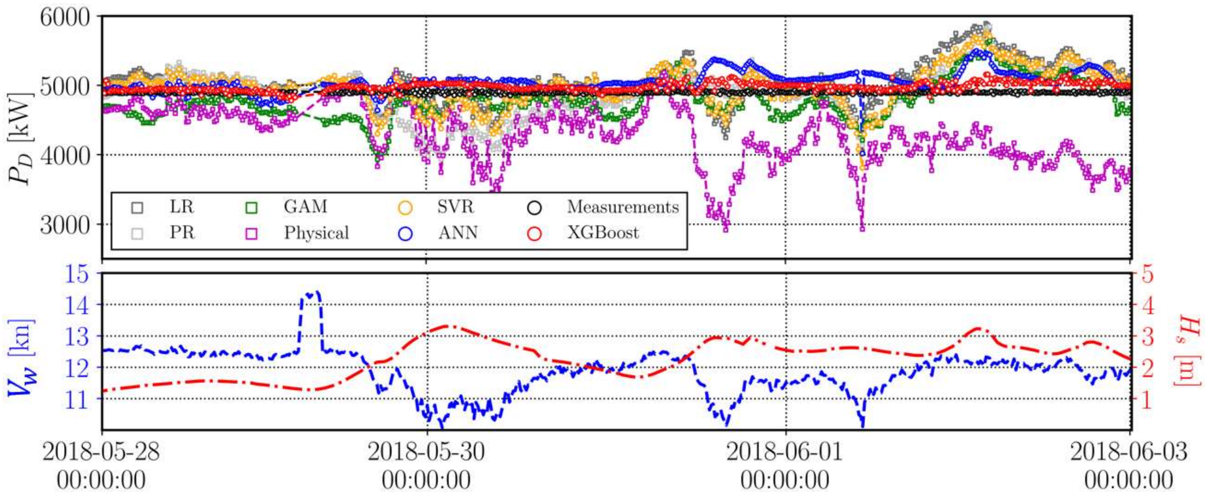

Figure 8 – Comparison of ship's propulsion power prediction by various models, as well as ship speed V_w, encountered significant wave height H_s along the case study voyage 2018-05-28.

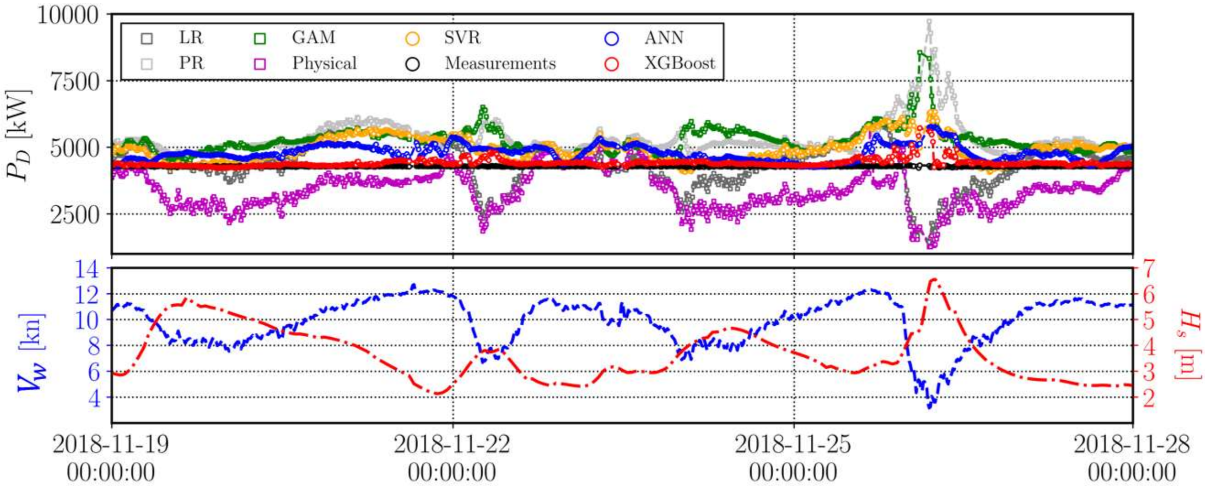

Figure 9 – Comparison of ship's propulsion power prediction by various models, as well as ship speed V_w, encountered significant wave height H_s along the case study voyage 2018-11-19.

Similar results are also observed for the unseen examples, i.e., voyage 2018-05-28 and voyage 2018-11-19, with even more significant speed variations during the voyages. It can be seen from Figure 8 and Figure 9 that the physical model significantly underestimates the powers. While the ship power predicted by the XGBoost model is consistently in line with the measured value. Except for an extreme case in voyage 2018-11-19, the ship encountered waves of nearly 7 meters of significant wave height on 2018-11-26. The ship speed was significantly reduced to below 4 knots. This large involuntary speed reduction is not fully captured by the data-driven model since the machine learning methods may need some extra parameters related to the navigation to be learned in the model. Furthermore, the ship speeds used for learning the data-driven model are mostly more than 5. This also puts additional limitations on the data-driven models. However, the prediction error from the XGBoost model of about 1000 kW is much smaller than the physical model and other models. The regression model performs poorly on the test data and has the worst prediction performance on the unseen voyages. For the data-derived models by ANN and SVR methods, their performance on the test set is as good as the performance of XGBoost model, but their prediction capability on the unseen voyages is very unstable. In some periods of those two case study voyages, the prediction errors of ANN and SVR models are similar to or even larger than the errors predicted by regression models.

3.2.2. Gray-box models

Approaches based on first principles or semi-empirical methods are often referred to as White-Box Models (WBMs). WBMs require lots of prior knowledge and physical principles, and the accuracy depends on assumptions and uncertainties implicit in the models. The data-driven regression/machine learning models belong to Black-Box Models (BBMs). BBMs are established using experimental or full-scale sailing data and are purely data-driven. BBMs do not require prior knowledge, but they do need a large number of full-scale measurements. The interpretability and extrapolation of BBMs are poor, which could lead to unexpected results for

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unseen data. A third model category, i.e., Grey-Box Models (GBMs), is classified. GBMs are developed based on the physical properties underlying WBMs, and knowledge from operational data in BBMs. Except for much fewer full-scale data requirements than BBMs, and higher accuracy than WBMs, GBMs also have good model interpretability and extrapolation capability, and can avoid unreasonable results for unseen data.

All current research on ship speed prediction is either BBM based on pure data, or WBM based on first principles. In this study, a novel physics-informed machine learning method is proposed to build GBM for the ship speed over ground prediction.

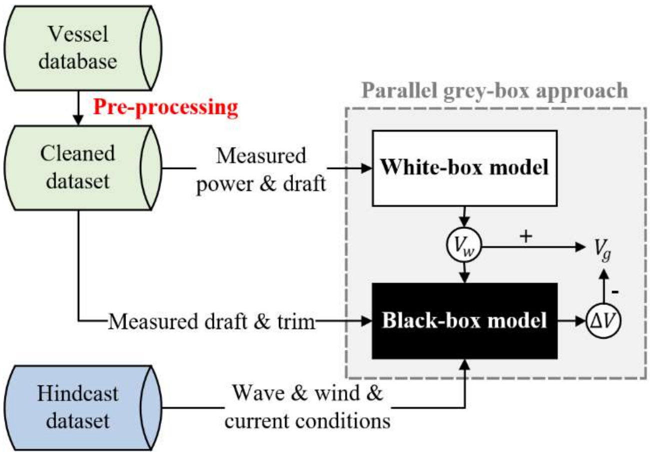

Figure 10. The parallel grey-box modeling procedure for ship speed over ground V_g prediction.

In this project, the physics-informed grey-box model is established by the parallel modeling architecture. The architecture of the approach is depicted in Figure 10. Configuring two models in parallel, the first of which is a white-box model that can derive the expected ship speed through water V_w based on measured propulsion power P_D, and ship draft T. Then the V_w is then fed into the black-box machine learning model. The black-box model modeling the speed reduction ΔV between the measured V_g and the white-box output V_w, based on both ship operational data and encountered ocean environment data. Then the grey-box model can output the speed over ground prediction by subtracting ΔV from V_w.

The white-box model outputs ship speed V_w (without any environmental loads) in terms of propulsion power P_D and draft T in calm water conditions. In this study, the $P_D - V_w - T$ relationship (known as baseline) is established by the Physics-Informed Neural Networks (PINNs) based on the towing tank model tests measurements. Figure 11 shows the solution surfaces of the propulsion power from the established partial differential equation (PDE). The trained PINNs can well capture the relationship between the propulsion power, ship draft, and the speed through water.

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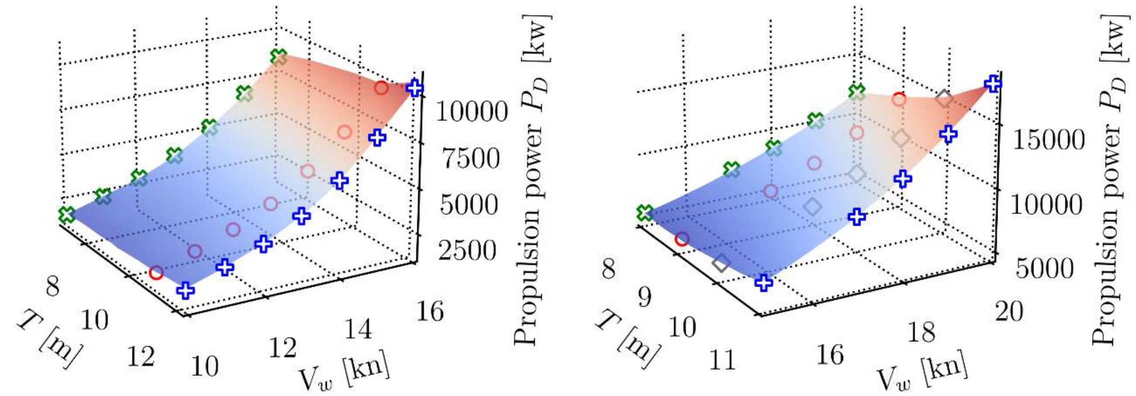

(a) the chemical tanker (b) the PCTC

Figure 11 – The physics-informed neural network (PINN) established PDE's solution surface at different drafts for (a) the chemical tanker, and (b) the PCTC.

Then the eXtreme Gradient Boosting (XGBoost) machine learning algorithm is integrated to estimate the ship's speed reduction under actual weather conditions. The proposed GBM has been compared against the traditional black-box model (BBM) using performance monitoring data, on 14 different unseen voyages.

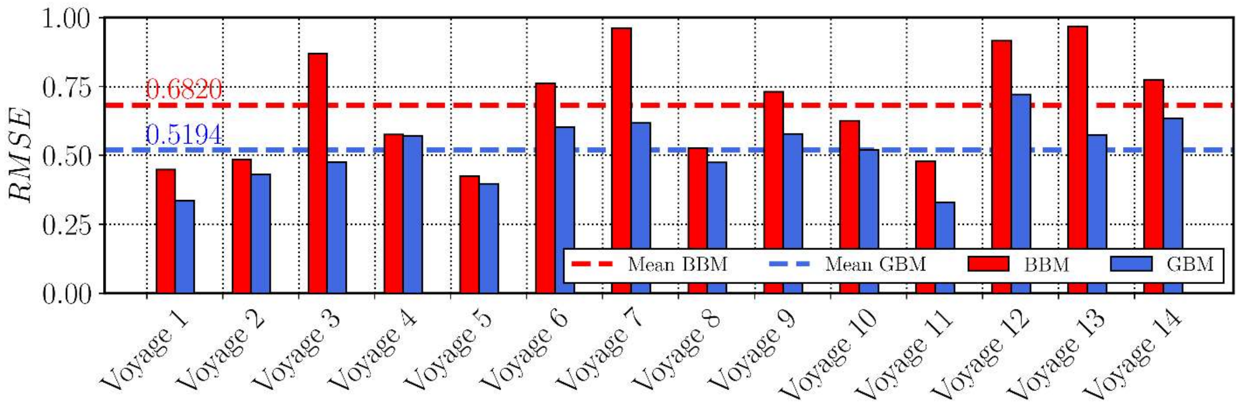

Figure 12 – The RMSE comparison for the different individual voyage as a test set case study for GBM and BBM of speed over ground V_g modeling, for the chemical tanker.

The *RMSE* comparison between BBM and GBM on different individual test voyage is presented in Figure 12. The proposed GBM has better V_g predictions for all the unseen test voyages. The mean value of the *RMSE* is 0.5194 for the GBM, and 0.6820 for the BBM, which is 30% higher. The result shows that the GBM has a better predictive capability than the pure BBM. Only voyage 2, voyage 4, and voyage 5 have similar *RMSE* for those two models, indicating that the training data can provide enough information for prediction in those conditions for BBM. However, at voyage 3, voyage 7, voyage 13, etc., the GBM improved the performance dramatically, due to the physical information added and enhanced prediction accuracy.

In reality, the model usually needs to accumulate measurement data and update itself dynamically during voyages, due to the lack of training data. This is known as continuous learning, i.e., recording new data and updating existing models in chronological order. To check the availability of performing continuous learning based on the GBM and BBM, we select several voyages of chemical tanker and use the data before each voyage to pre-train the models. The continuous learning is then carried out as data updating. Figure 13 presents one case study continuous learning comparison for voyage 2017-04-07. The models are trained only using two years' measurements before 2017-04-07. The results of GBM are very close to the measured values, but BBM underestimates the speed. It shows that the GBM can approximate the measured values more efficiently when the training data is limited.

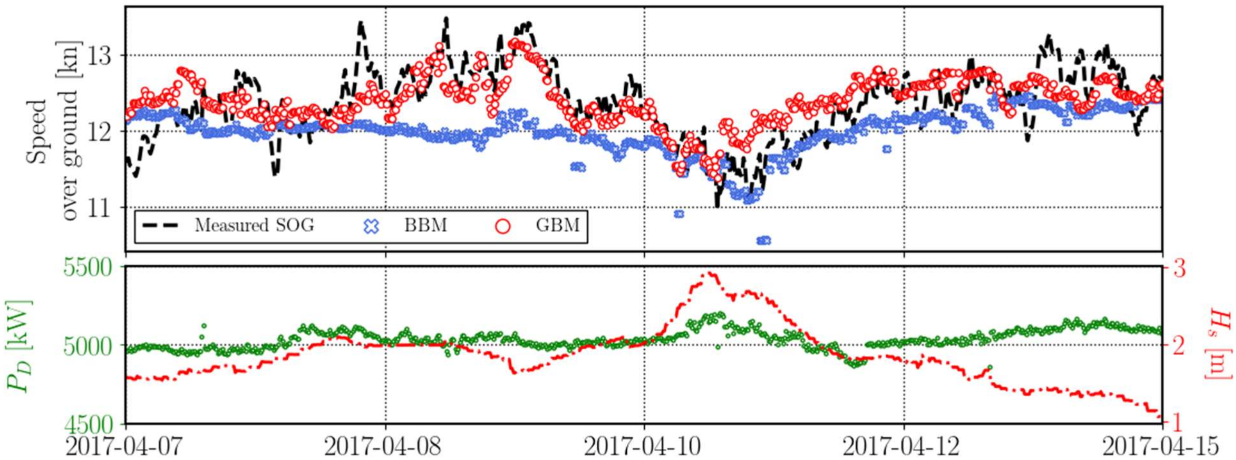

Figure 13 – Comparison of speed over ground prediction V_g by BBM and GBM continuous learning, as well as ship propulsion power P_D, encountered significant wave height H_s along the case study voyage.

3.3. Social science research (Halmstad University and University of Gothenburg)

The overarching aim of the social science part of the project has been situated in the same general area of inquiry as the project in its entirety, i.e., how can large datasets from cargo ships be utilized to increase energy efficiency and reduce emission in sea voyages. The social science component recognizes that making transportation more rational and energy efficient does not only require technical measures but that a successful implementation of new technology also requires certain managerial practices and an organizational structure that facilitates the transition and change and that ensures user understanding and acceptability. It is also important that the artefacts developed and produced are suitable and designed with regard to the users' practices and knowledge. As stated in the application to Trafikverket, the social science part is "important as new technology does not guarantee that improvements will

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take place in practice – unless the methods of technical development produce products that are well adapted to existing working methods, requirements, and conditions.”

As such the social science part of the project has aimed to investigate how the new digital tools can be made useful and adopted in the planning and execution of daily operations in the shipping industry (through the participating shipping companies). To add additional knowledge on the possibilities of increasing energy efficiency in the shipping industry the project has also gathered data on the development of AI algorithms, to increase or understanding of possible obstacles for a successful implementation. The hope was to gain knowledge on the views and practices of stakeholders at various levels in the actor network of commercial cargo shipping, knowledge that is useful for understanding how this and similar AI support systems can be utilized to increase energy efficiency in shipping.

Martin Viktorelius and Simon Larsson have been collecting empirical data for the social science project component throughout the duration of the project. Data has been collected through i) participation in bi-weekly project meetings throughout the project, ii) participant observations in SCRUM-meetings with technical developers, iii) interviews with project participants, iv) participation in meetings with potential future users of the new Route Pilot (*Slipstream* integration with Fleet Analytics) including shipping companies and charter departments, v) observations and interviews with crew on cargo ship through telephone, zoom video conference, and on board on ships (fig 1). This data has provided an empirical foundation for the analysis. The collected data was analyzed in accordance with the overarching aim of the research project, i.e., how ML system can feed into current praxis of executing sea voyages (Viktorelius & Larsson 2021; Viktorelius & Larsson 2022b). But the data was also analyzed in conjunction to the contemporary debate on social dimensions of AI, and from this departure point we analyze various challenges that occur in the process of technological development

Figure 14 – Fieldwork onboard UECC Autostar

and early stages of implementation (Larsson et al. 2023), and some epistemic aspects of machine learning technology (Larsson & Viktorelius 2022).

In addition, several workshops have been held with the developers in the project to offer feedback on the implementation and technical product from the perspective of users and recipient companies as analyzed by us (Simon Larsson and Martin Viktorelius).

The scientific results have been published in scientific journals and presented on conferences and workshops to a wide range of researchers within different disciplines. An international data-sharing project on energy efficiency in shipping was performed within the scope of this project. In this collaboration, researchers from Nordic countries (four universities) compiled extensive ethnographic data and wrote a joint publication on the constraints of implementing energy efficiency in shipping (Poulsen et al. 2022).

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4. Results

The result is presented in sections related to the development and implementation of the project and the two research fields.

4.1. Development and implementation (Yara Marine and Molflow)

The development part of the project was able to reach all the way in providing the users with a working tool for optimizing voyages, implemented and used onboard.

4.1.1. Development

At the end of the project's allocated time the following functions have been developed and deployed into digital production environment:
An interface for the user to import and store route files (.rtz format) which subsequently could be used for optimization. The routes consist of waypoints and can contain additional constrains for taking special navigational circumstances into consideration (e.g. speed limits between certain waypoints)
An interface for creating, managing and optimizing schedules. Schedules is the name chosen for the part of a voyage to be optimized. Creating a schedule includes setting the basic optimization parameters: ETA, ETD, start and end point of voyage, and vessel draft.
An API between the user interface (Fleet Analytics) and the modeling and optimization engine (Slipstream) that enables the user to repeat the optimization procedure any number of times and as frequently as required.
Functionality to identify where along the voyage a vessel currently is located and re-optimize the instructions from that point in time and position.
A result view that clearly shows the expected outcome of the optimized schedule to the user. This includes displaying the predicted future speed, weather impact, current impact, and the recommended instructions to execute expressed either in power or fuel consumption.
Feedback from users onboard throughout the project proved very useful in understanding improvements and changes that need to be made in order to truly adopt an AI-based into the daily routine of operating a vessel. Here, the field work of Martin Viktorelius and Simon Larsson was also very important. However, the time and resources available in the project were not enough to implement all these changes and improvements and evaluate their impact. The following functionality was identified as items that would have improved the user experience further:
Better user guidance through alerting when optimization parameters were not entered in a way matching the actual voyage parameters. An example being that the tool checks if the optimized ETD (estimated departure time) matched the actual departure time of the vessel once the voyage is started. If not a recommendation to re-optimize could be given.
Grouping schedules belonging to the same voyage would have created a better overview of how the tool was used during a voyage and which decisions to re-optimize were made by the crew.
Assigning statuses to schedules showing if they were executed or not would have created a much clearer picture of the workflow and decision making of the crew.

Tools for simplified re-simulation of an ongoing voyage, related to updated weather forecast or changed operational instructions.
System integration between the web-based optimization tool and the onboard execution tool (FuelOpt) was originally part of the development plan for the project. This functionality had to be replaced by other development goals. It would however have been a useful functionality to eliminate some of the user errors in aligning optimizations with the actual voyage.

4.1.2. Onboard implementation

The result of the implementation phase was quite different between the two vessels. This section describes the two separate vessel implementations individually.

4.1.2.1. AutoStar

The vessel AutoStar (a car carrier) adopted the tool easily and the vessel is now calculating and optimizing voyages as part of their daily routine. During the project Auto Star made over 400 optimizations with Fleet Analytics and Slipstream. Figure 13 and 14 show two of many optimizations done and followed.

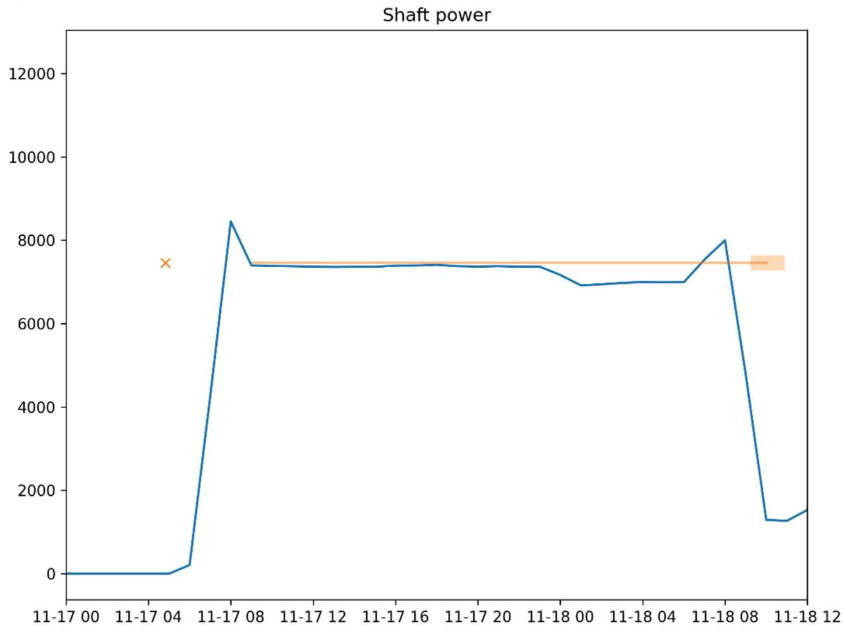

Figure 15 – An Auto Star route planned a couple hours before execution (yellow x-mark). Yellow line is planned route from “start of sea passage” to “end of sea passage”. Blue line is Auto Star’s propulsion power. The yellow area in the end of the route marks the inaccuracy of the optimization. Note the blue bump

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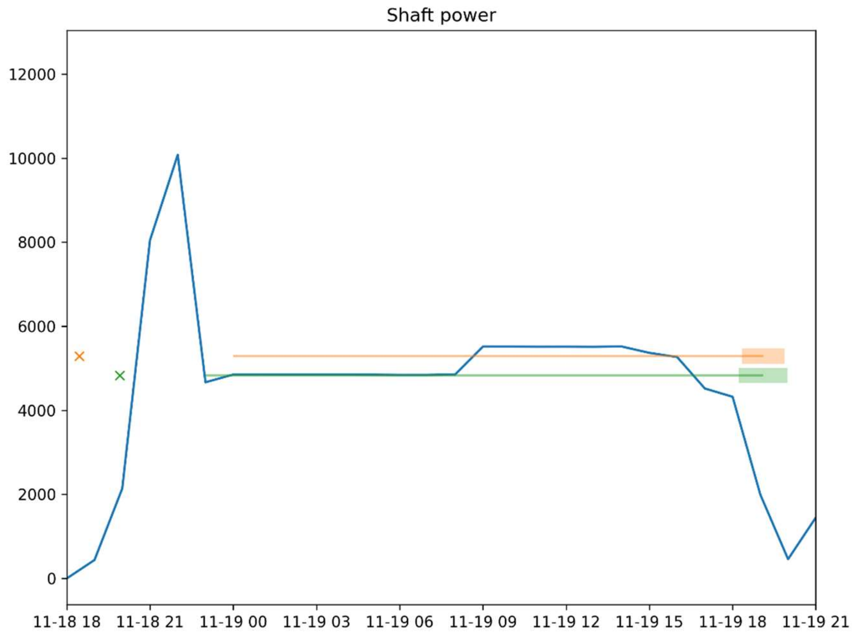

Figure 16 – Another route executed this autumn, Here the crew have two optimizations, the first yellow indicate slightly later start of sea passage, the green done just before leaving port with an earlier start thus lower shaft power. Note that during the route crew decided to follow the first optimization for unknown reasons.

4.1.2.2. Sten Hidra

The vessel Sten Hidra (a chemical tanker) did not end up adopting the tool as routine for several reasons. Early in the implementation process it was understood that the crew already had a very solid and established way of operating their voyages which they considered practical for their purpose. Also, the crew were not immediately convinced that the voyage optimization provided by the project would be beneficial.

It is important to point out that the vessel is trading in the spot market with very unpredictable, often short, routes and schedules. As a result, the vessel's voyage instructions did not always prioritize minimizing fuel consumption. This meant that not all voyages were considered interesting to optimize which constituted a barrier for making the tool part of the onboard routine.

This highlights a very important success factor for any activity that aims to challenge an established routine. Most, if not all, stakeholders of the activity need to be supporting the change. In the case of Sten Hidra, the optimization requirement could have come early on from the chartering department who lays the foundation for the operational instructions. Early in the project, the vessels' chartering department received a presentation of the project, but it was decided to focus on implementing the tools onboard the vessel only.

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4.2. Technical research (Chalmers)

For the ship speed propulsion prediction by machine learning black-box techniques, based on the comparison of the test set, the XGBoost model has achieved much better predictive ability than statistical regression models. Compared with artificial neural network and support vector regression, despite the predictive capability of the XGBoost model is slightly better, and the training time required is only or less than one-tenth. For the validation on unseen sailing voyages, the XGBoost model has very good prediction results, whereas the artificial neural network and support vector regression models have much higher prediction errors and are not stable in the time series. In brief, the XGBoost model has the most stable and reliable predictive ability, with the highest model training efficiency suitable for onboard devices.

The XGBoost model is applied for further analysis and discussion, and it is able to derive the ship speed-power baseline yearly or for a several years' span. Based on the sensitivity study, one year data volume can establish a more solid data-driven ship speed-power model. And the stationary period no larger than 1 hour is suggested for the machine learning modelling.

For the physic-informed grey-box ship speed prediction model, the GBM can improve the prediction accuracy by about 30% for the chemical tanker with five-year abundant data compared to the traditional BBM. Moreover, the GBM can approximate the measured values more efficiently when the training data is limited. Then the comparison between the proposed GBM and pure BBM is conducted for further analysis for ETA estimation, see Figure 17

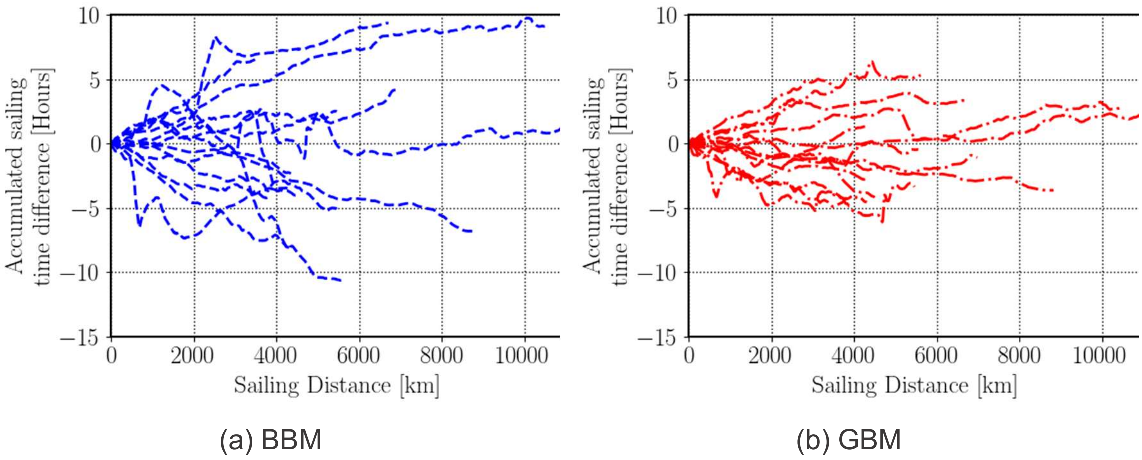

Figure 17 – The accumulated error in sailing time for (a) the BBM and (b) the GBM of all 14 sailing voyages of the case study chemical tanker.

Figure 17(a) presents accumulated sailing time difference of different voyages for the BBM, and Figure 17(b) present the results for the proposed GBM. Obviously, the time differences from BBM diverge widely as the sailing distance increasing, and the maximum difference exceeds 10 hours. The sailing time estimated by the GBM is much closer to the real ETA, and the dashed lines concentrate in a smaller range. The biggest discrepancy of GBM is about 5 hours, which is 50% less than the BBM.

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4.3. Social science

The results of the project are presented as scholarly articles (Larsson & Viktorelius 2022; Larsson et al. 2023; Viktorelius et al. 2022b; Poulsen et al. 2022), conference presentations (Larsson 2022a; Viktorelius & Larsson 2021; Viktorelius & Larsson 2022), and a presentation on a workshop (Larsson 2022), as well as a report that make results available in a technology-neutral way, which other shipping companies can use in their processes to implement similar decision and support systems. In particular, the process of automating ship journeys will be addressed, which is of general relevance also for issues beyond energy efficiency, such as safety issues (Larsson & Viktorelius 2022b). Below follows a summary of the main points of our study.

Aligned with what was expected it is not a straightforward task to implement a machine learning system and make captains use it in their daily routines. While the use and user-interface was considered easy to use by captains the system introduced an increased degree of psychological uncertainty for arriving on time for the delivery slot in the harbor (see technical description of system). This was exacerbated by the fact that captains were often used to operate ships on a fixed speed over ground that provides a nearly exact estimated arrival time. In the few trails that were executed within the project captains were sometimes hesitant to trust the predictions made by the system. The main given reason was that they did not find the machine prediction to be aligned with what they would expect based on their own knowledge and experience. In the case of this project accuracy of predictions is an important variable for determining use in the long run—at least from the perspectives of the individual captains. However, too few real-life trails were conducted within the project for a thorough evaluation of the actual accuracy (as shown in practice as opposed to theoretical calculation) and the factors that might increase or decrease acceptability of captains and other end users of the system.

Importantly, the results show that the motivation to use advanced planning tools, or to change practices, does not emerge directly from technical potential but has to be translated and constructed through the social interactions and social systems (work orders) in which the technology is embedded. The development of machine learning technologies requires advanced and specific competences and knowledge that differs from the target domains of the users (such as ship navigation). For this reason, increased communication and exchange between technologists and practitioners is needed to create a mutual ground for making sense and meaning of artificial intelligence in practice. The logic of the practitioners' (captains, charterers, operators) practice needs also be accounted for in the development of technology, which is why communication is needed in both directions early on in these types of projects.

Furthermore, addressing organizational (structural) factors that might hinder the successful implementation and long-term use of the system are also important in addition to the social acceptance and understanding from captains and managers. From the studies it became evident that several organizational obstacles need to be addressed for a successful implementation of this and similar ML systems in the shipping industry. The basic premise of the project is that a fixed power consumption with varying speed saves fuel – on the average trip. This will lead to increased inaccuracies in arrival time and in the interviews there is a general opinion that many harbors aren't adapted to varying arrival times which might lead to delays and in some cases fines. Another organizational obstacle is that charter party agreements sometimes stipulate a fixed speed which makes varying speed difficult to use in some contexts. Furthermore, one charter department did not seem interested in energy optimization and in lowering fuel prize for each transport. This is because the fuel cost is generally calculated on a yearly average and not on each trip. The organization of the way ships are owned, booked, and operated result in that many actors have little or no incentive to reduce fuel in their daily practices. In sum, because the way ships are operated is situated in a larger context (e.g., management, charter departments, harbors and regulation) a full utilization of the ML system requires top-down changes and do not rely solely of the experience of the captains. That is, a successful implementation requires institutional changes in the industry in addition to engagement and genuine interest from the shipping company and the charter departments.

As stated above, the social science part of this project has also studied the technical development through participant observations and interviews. From the developer's side we have been able to study the work of collecting data, curating data, data wrangling and training of models, as well as the development of a user interface integrated in Fleet Analytic. These data collections have provided insights in technical obstacles and details are intertwined with praxis in the industry (Larsson & Viktorelius 2022; Viktorelius & Larsson 2021). For example the technical features of the ML system are not adapted to planning trips a long time before departure because weather prognosis that is a part of the data processed through the ML algorithms tend to be inaccurate. Also, the actions of the crews affect the quality of the data, for example if the ship has been operating for a long duration of time in certain condition (for example on a specific speed or a specific engine setting) the model trained on this ship is not good at making predictions for voyages in other conditions. Another example is that certain operations might decrease the likelihood of identifying correlations such as an irregular use of fins (used to stabilize the ship in though weather conditions).

By studying the development, we have not only been able to identify how social/organizational factors are influencing the technical outcome, but also the work done by the developers in visualizing and making the ML predictions intelligible to (imagined) end users. In this work we identified difficulties involved in translating and explaining and making data useful in the context of the shipping industry. For example derived from the difficulties in interpreting and evaluating statistical data in everyday evaluations. This has enabled us to make an intervention in the scholarly debate on the design of machine learning system and how data scientists become the translators between two fields of inquiry (Larsson 2022; Larsson & Viktorelius 2022b).

Based on the all the data collection in this project we have also been able to study how problematizations (i.e., how something is being considered or treated as a problem) occurs in the field of AI technology. As such we have written an article about how commonly discussed AI dysfunctions (such as opacity, inaccuracies in predictions, user safety, resistance) are understood and negotiated within this project. Knowledge has been gained about how AI related problematizations are formulated in organizations. It contributes valuable knowledge to complement existing social science (and interdisciplinary) literature on AI related dysfunctions. This result is a scholarly article submitted to *Artificial Intelligence* (Elsivier) titled Relational problematizations: A framework for studying AI dysfunctions (Larsson et al. 2023).

All and all the social science part of the project has contributed knowledge to the methods, areas of use and effects of digitalization, automation and machine learning. This is necessary to be able to develop technology that really supports the optimization. New knowledge about actual needs and concrete areas of use for digitization and AI is therefore a crucial component in the development of new technology with the aim of optimizing the planning and execution of maritime operations. While social/organizational challenges were expected results of our inquiry, the study has contributed with unique knowledge as to how such factors influence the development and implementation of an AI system in shipping.

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5. Discussion and further work

In this section, reflections on the project by Yara Marine, Molflow, and Halmstad University with University of Gothenburg are provided. Yara Marine, Molflow and Chalmers have already started a separate technical project to continue with some of the findings in this project, which was funded by Vinnova. Halmstad University and the University of Gothenburg have continued to be part of the meetings in this new Vinnova project to monitor the developments. They have just submitted a new application to Trafikverket for continued social science research in this area.

5.1. Yara Marine Technologies

Throughout the project, several insights into both internal processes and important considerations for working with vessels and operational stakeholders have been gained.

Most notably, the tool that was developed and put into the hands of crew members has also become an important part of YMT's toolbox when presenting a shipowner with arguments for changing their behavior to focus more on fuel consumption and emissions. The AI based models are very suitable for assessing the impact of different operational modes for a vessel. The ability to showcase the potential of a new way of operating will increase the likelihood of adopting such methods. This project focused on directly implementing the tools on-board but the tools have shown to be equally important for other stakeholders to understand the value of a new way of operating.

The project also showed the importance of complementing new technology and tools with guidance and handholding. It was made very clear throughout the project that there are strong traditions and routines in place that govern a vessels' and crew's operational pattern. YMT has realized the need for delivering close and frequent operational support and has reacted to this need by establishing a new sub-department with the role of guiding customers to a best operational practice.

The research by Halmstad University and University of Gothenburg showed how important it is that the tools support the existing operation and responsibilities of the crew. For future work, YMT intends to find ways to avoid obstacles in the crews' workflows by more tightly integrate the onboard optimization system and its interaction with the result of the model. For example, it would be good to further develop automated functionality where the state of the executing schedule can trigger re-simulations to serve the crew and people in office with updated and relevant prognosis of the voyage (arrival time and energy consumption) and any changes to the recommended settings. As an illustration to this problem: it was discovered that crew may do simulations assuming they would sail at a certain time, but actually sail a few hours later. This would result in errors in reaching the arrival time, as the ship would not encounter the forecasted weather at the expected place along the route. Another aspect is that if the weather forecast does not match the encountered weather, it would be beneficial for the crew if this was signalled by the system itself, triggering a need for a new updated simulation. However, for this to work this needs to be done with careful consideration on aspects of cybersecurity and also maintaining critical interactions with the onboard crew. Cybersecurity issues become relevant as the system onboard would need to be integrated with internet cloud solutions.

On a higher level, it could have been better for the project to have one more shipping company in operation with time-table critical arrival times. This would have given one more case study where the crew would have been even more interested in adopting the new tools. In this project there was limitation in how the tools was tested out for the other vessels, both due to the available resources and time but also that the tools was not critical for the crew and its daily operation in more flexible arrival time spot market.

In summary, the project has given great insight into new technology and there are strategies on how to further develop solutions that has the potential to be very central to the customers, contributing with additional value to the business and helping to bring down the emissions even further and improve the carbon intensity index score (CII).

5.2. Molflow

Direct contact with ship operators is important. During the project we have discussed many important topics. The two most interesting from Molflow's perspective is, 1) What are the capabilities of the ship model and what is its limitations? 2) How much is saved when using this type of route optimizations.

The first topic "capabilities and limitations" is interesting due to its technical perspective. Since the models in slipstream are data driven – data quality from the ship's sensor is a very important factor. But, the setup of the machine learning system play a large role in how a ship model can learn from data. There are "soft perspectives" in capabilities and limitations also – how do we explain technical limitations to the users, so users can intuitively see or understand when the ship model makes the wrong decision? One technical solution is of course to ensure that the models never fail.

The second topic "how much did I save?", is hard to answer. In this case it would be good to have a standardized way to calculate savings – this is not only good for service providers, but for the clients as well. It would then be possible to compare different optimization solutions.

5.3. Social science

Collaborating in an interdisciplinary project is very enriching for social science researchers. It is productive to work with people from technical disciplines that are knowledgeable and can provide both access and knowledge that is relevant in the study of social dimensions of technology. In future project we would consider it relevant to have closer connections between the social science part of the project and the technical part, so that the technical development can be done in a way that maximizes the possibilities of collecting relevant data and that the social science part could feed in more into the technical development.

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6. Conclusions

The project set out to find a way to "realize the most energy-efficient voyage in practice". This was in recognition that there were many solutions and a lot of research papers out there about *calculating* efficient voyages, with ever advanced methods, but not enough about how to put those calculations into use onboard actual vessels. Yara Marine, the project manager of this project, had a solution which enabled more energy efficient voyages, but to realize *the most* energy-efficient voyage, additional systems were needed. On the engineering research side, there was a thus a parallel need to be able to develop and especially test new methods. On the social science side, implementation of AI onboard represented a new and exciting research field that still tied closely with previous work on automation in workplaces.

The project developed and implemented a solution onboard vessels of two different kinds of shipping companies, one car carrier, sailing on a time table, and one product tanker sailing on tramp shipping. The implementation was especially successful on the car carrier, with the crew still using the tool 6 months after the actual trial ended. On the product tanker, it was more difficult to implement the existing tool due to different operational profile in a spot market. However, further work will address this and develop features aiming to be a solution to these different needs.

Yara Marine, Molflow and the social science researchers at Halmstad University and University of Gothenburg all learned from the development and the implementation. Several ideas for further work have been generated. The results have and will be published in academic papers and will also be published in a separate guideline for implementation of AI systems onboard later this year (pending publication in academic journals first).

For Chalmers, the project meant that data was made available from ships in operation to further develop and test more advanced models than what is currently used. In a continued project, funded by Vinnova, the partners are looking into implementing findings from that research in the developed system. In this continued project, great emphasis has also been put on developing a method for verifying the effects of this kind of system. The current project showed how dependent savings are on current operational practices.

The results of the project have also been put into use in a commercial product by Yara Marine Technologies, called Route Pilot AI.

Knowledge grows

7. Academic publications and presentations from this project

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