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Toward Digitalization of Fishing Vessels to Achieve Higher Environmental and Economic Sustainability

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ABSTRACT: Fishing vessels need to adapt to and mitigate climate changes, but solution development requires better information about the environment and vessel operations. Even if ships generate large amounts of potentially useful data, there is a large variety of sources and formats. This lack of standardization makes identification and use of key data challenging and hinders its use in improving operational performance and vessel design. The work described in this paper aims to provide cost-effective tools for systematic data acquisition for fishing vessels, supporting digitalization of the fishing vessel operation and performance monitoring. This digitalization is needed to facilitate the reduction of emissions as a critical environmental problem and industry costs critical for industry sustainability. The resulting monitoring system interfaces onboard systems and sensors, processes the data, and makes it available in a shared onboard data space. From this data space, 209 signals are recorded at different frequencies and uploaded to onshore servers for postprocessing. The collected data describe both ship operation, onboard energy system, and the surrounding environment. Nine of the oceanographic variables have been preselected to be potentially useful for public scientific repositories, such as Copernicus and EMODnet. The data are also used for fuel prediction models, species distribution models, and route optimization models.

KEYWORDS: Tuna fishery, fisheries digitalization, climate change mitigation, environmental science, technology research, data science, sustainable systems
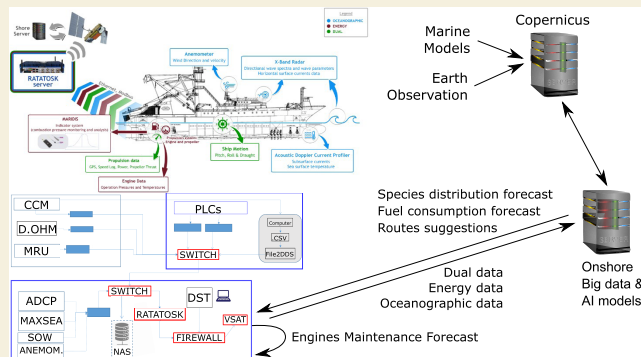
1. INTRODUCTION

The United Nations development goals require fishing to be environmentally friendly, economically viable, and socially sustainable to provide long-term food security. The fisheries industry needs to reduce its costs and carbon footprint to achieve such objectives. Fuel consumption may represent 50% of the total operational costs of the tuna vessels, which is being one of the main concerns of the fishing companies.[1,2] Moreover, the world fishing industry emissions per landed ton of fish have recently increased by 21% recently.[3] A total amount of 3 billion liters of fuel is consumed in a year by the world's fishing fleets.[4] But as large pelagic fish, such as tuna species, are highly migratory, vessels targeting tuna species tend to have higher and more variable fuel consumption costs than other fishing of coastal species.[5] This involves the yearly emission of 7.7 billion tons of $CO_{2\ equiv}$ into the atmosphere by the tuna purse seine fleet in fishing operations. The changing tuna fish distribution[6,7] and human behavior modulate fuel consumption,[7] which in turn influences both the profitability and sustainability of the fisheries industry and impact on the ecosystem through greenhouse emissions.

As an example, from the world's largest commercial fisheries,[8] the tropical tuna fishing industry is starting to use Earth Observation (EO) data to characterize the environmental conditions of the surrounding areas in order to locate fishing grounds with less effort (i.e., time, fuel, and costs). Digitalization of tuna vessels means that their capacity to record data and to use existing EO data has increased. However, due to the large volume, diversity of sources, and quality of recorded data, they are sparsely stored and used, leaving much of the already recorded data intact and unstructured. Consequently, data are not often used for further analysis or integrated into holistic energy management. Big data methodologies seem to be the solution to deal with such a large volume of data and exploit it efficiently to turn it into useful information.

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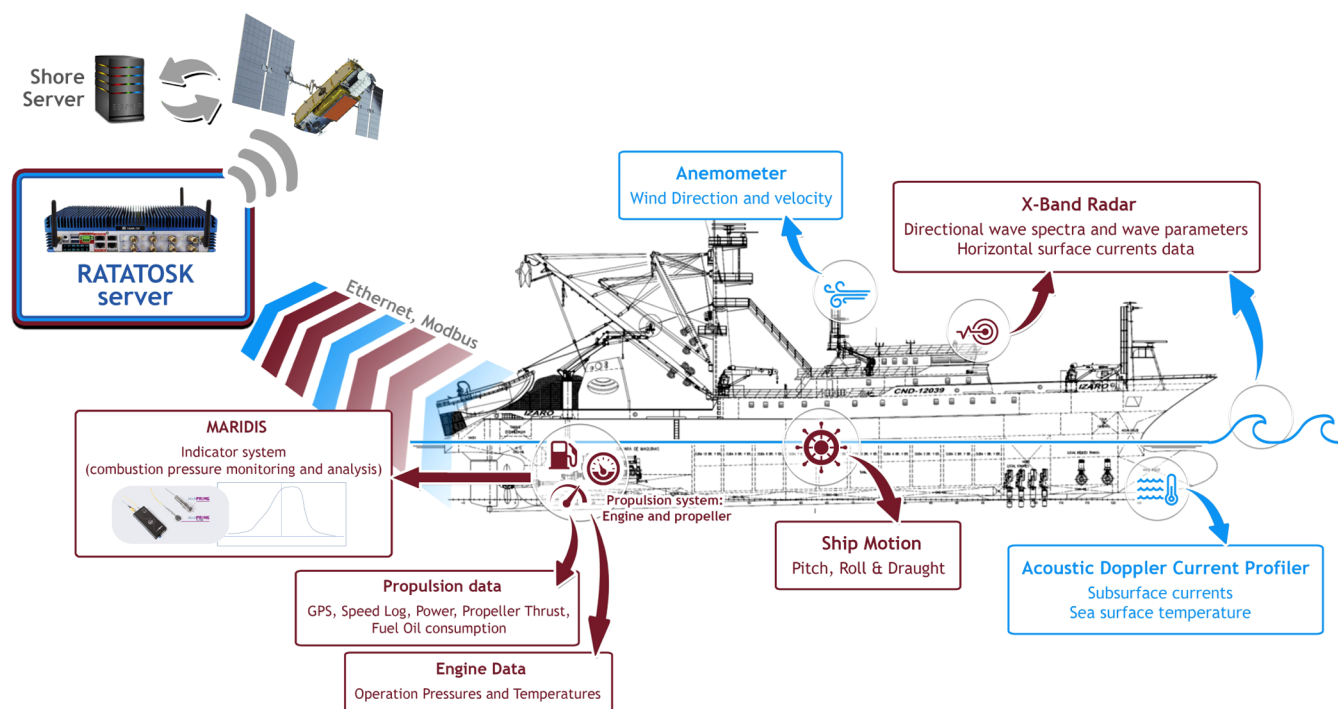
Figure 1. Data acquisition and monitoring system scheme. Components measuring oceanographic data are shown in blue, components measuring energy consumption in red, and in green dual components needed for data synchronization or to consider when using oceanographic and energy data measurements.

Solving these problems demands new system architectures for data acquisition, transmission, storage, and large-scale data processing mechanisms.[9] Big data processing techniques, enhanced by machine learning methods, can increase the value of such data and their applicability to society, industry, and management challenges. Machine learning has already proved its potential in marine sciences and fisheries such as the examples in fisheries forecasting,[10] automatic classification of samples,[11] marine spatial planning for resolving conflicts of fisheries and new activities,[12] fishing activities tracking,[13,14] indicators, fishing gear selectivity[15,16] or species identification.[16] In addition, evolving optimization heuristics have been designed in recent years to help tropical tuna fishing vessels.[17] However, its use by the fishing industry is behind the state-of-the-art and day-to-day applications, as compared with the other shipping industries.[18−20]

There is a growing need in fisheries science and management for larger amounts of data and highly trained experts in which digitalization and AI should play a central role. Digitalization refers to enabling or improving processes by using digital technologies and data. As the basis of digitalization, these data must be collected, stored, and managed in a single platform from which a harmonized data set can be transmitted to different users and for different data analyses. Therefore, the digitalization in this sector is very important for achieving these purposes, and AI systems could play a critical role in the acquisition and use of the data.[21] Four main challenges that can explain the lack of digitalization in the fisheries industry are up-front costs and insufficient access to capital, legal, and bureaucratic barriers; failure to implement data collection standards; and lack of trust and buy-in from fisheries.[22] In this work, the challenges of digitalizing a fishing vessel for scientific data collection will be demonstrated.

Fishing vessels are notoriously heterogeneous with respect to onboard installed sensors, data protocols, and network topology. This is a major obstacle common in big data problems[9] for both collecting data from vessels and also for local data exchange onboard vessels. It implies a non-harmonized data collection and recording with a tailor-made and ad hoc integration against individual sensors instead of interfacing a central hub, which again integrates against the individual sensors and onboard systems. In effect, this makes it difficult to achieve the otherwise usual large-scale synergies found in other kinds of industrial processes. The aim of this work is to describe how the integration of data for the development of fuel consumption models, species distribution models, and routing strategies could be achieved that can help the industry to mitigate and adapt to climate change.

## 2. METHODS FOR A FISHING VESSEL MONITORING SYSTEM

The target of digitalization onboard the fishing vessel is to characterize the vessel performance under different operational conditions to reduce greenhouse and pollutant gases and to provide data to improve fishing operations. Hence, the data collected include parameters that define when and where the fuel has been consumed. The "where" parameter should also include metrics that can be used to characterize the environmental conditions when fuel oil was consumed during sailing operation (going from one geographical point to another) and when fish was caught (sailing condition and fishing condition). Fishing vessels may also act as oceanographic data acquisition systems contributing to the ocean forecasts, which are used to improve operational efficiency.

According to the targets described above, the systems and data have been grouped in three main categories to facilitate their understanding (Figure 1). Two of these categories are related to the type of data being captured: environmental or oceanographic (outside of the vessel) and propulsion related (inside of the vessel). Both types of data are needed to build fuel oil consumption (FOC) forecasting

Table 1. Devices and Their Types of Data[a]

group of data	measuring devices	description	acquisition rate	remark	variable qty
environment	ADCP with temperature sensor	four different underwater layer current velocity and direction at different depths, surface water temperature.	medium (1 Hz)	onboard	4
	anemometer	wind velocity and direction.	medium (1 Hz)	new	5
vessel	engine sensors	engine op. parameters: pressure, temperature, and speed.	low (0.1 Hz)	new	62
	delta OHM	engine room ambient conditions (pressure, temperature, humidity)	medium (1 Hz)	new	4
	MarPrime	engine combustion parameters	high (200 kHz)	new	74
	propulsion/fuel consumption	propeller power and thrust, fuel oil consumption.	medium (1 Hz)	onboard	12
	PMS (power management system)	ship electric consumption and generation	medium (1 Hz)	onboard	10
	GPS	position latitude, longitude, speed over dround (SOG), course over ground (COG).	medium (1 Hz)	onboard	7
	speed Log	speed over water.	medium (1 Hz)	onboard	2
	motion reference unit	ship motions.	high (10 Hz)	new	13
integration, network, and backup	ratatosk	above data integrator	configurable	new	does not apply
	NMEA-2000 to ethernet converter	data convert from NMEA to ethernet		new	
	serial to modbus ethernet converter	data convert from serial to modbus		new	
	can J1939 to modbus ethernet	data convert from J1939 to modbus		new	
	ethernet switch	networks connection		new	
	NAS	backup storage		new	

[a]New (new device to be installed in the project)/onboard (system already installed in vessels).
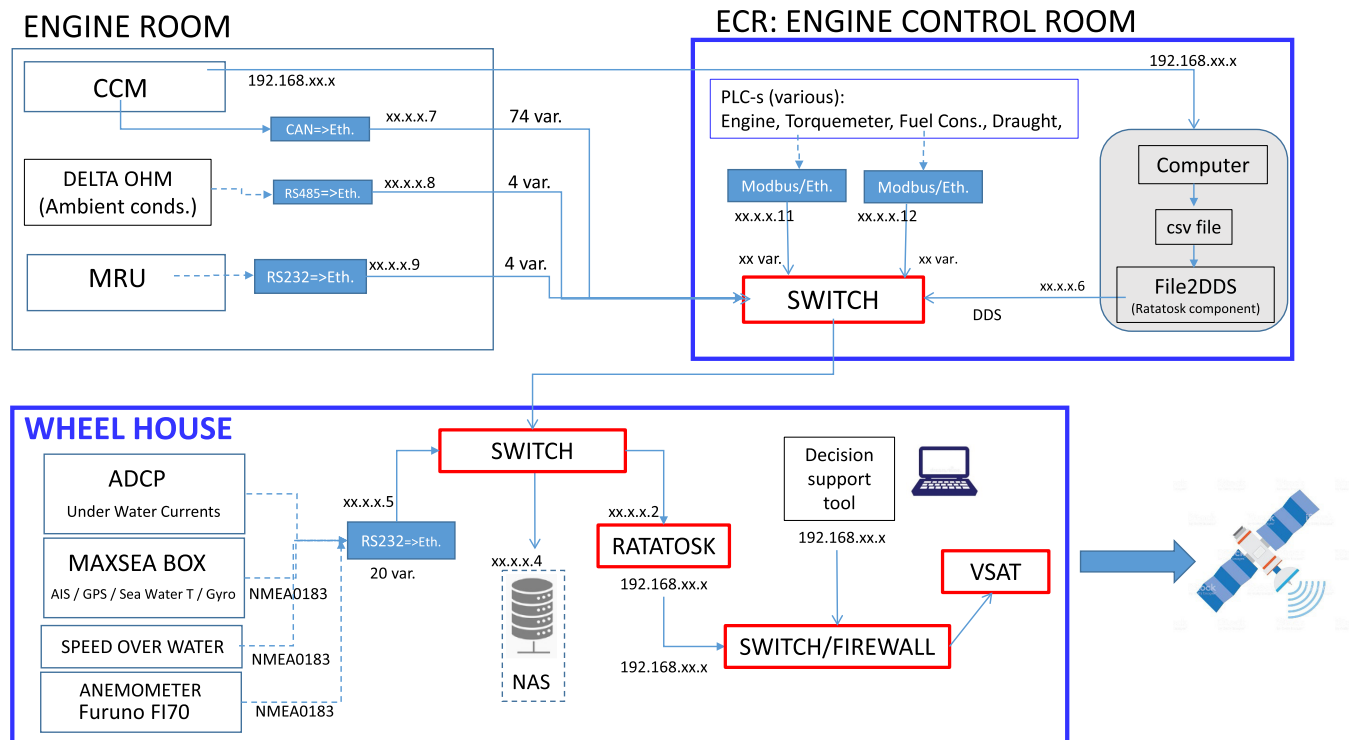

Figure 2. Onboard installation scheme showing the main components organized by ship location.

models using a statistical approach,[23−25] a machine learning approach,[26−32] or combined with optimization methods.[33] A third group integrates other devices that help data integration or produce data relevant for environmental and propulsion forecasting models (e.g., timestamps or vessel position). All these data are crucial to develop routing decision support systems that can reduce fuel

consumption and consequent emissions[33−36] particularly for fisheries where such systems are sparse.[37] In total, 217 variables are recorded, of which 191 propulsion-related variables, 17 environmental variables, and nine from the third group of variables (Table 1).

Definition of variables needed to evaluate the vessel fuel oil consumption performance during free sailing operation has been
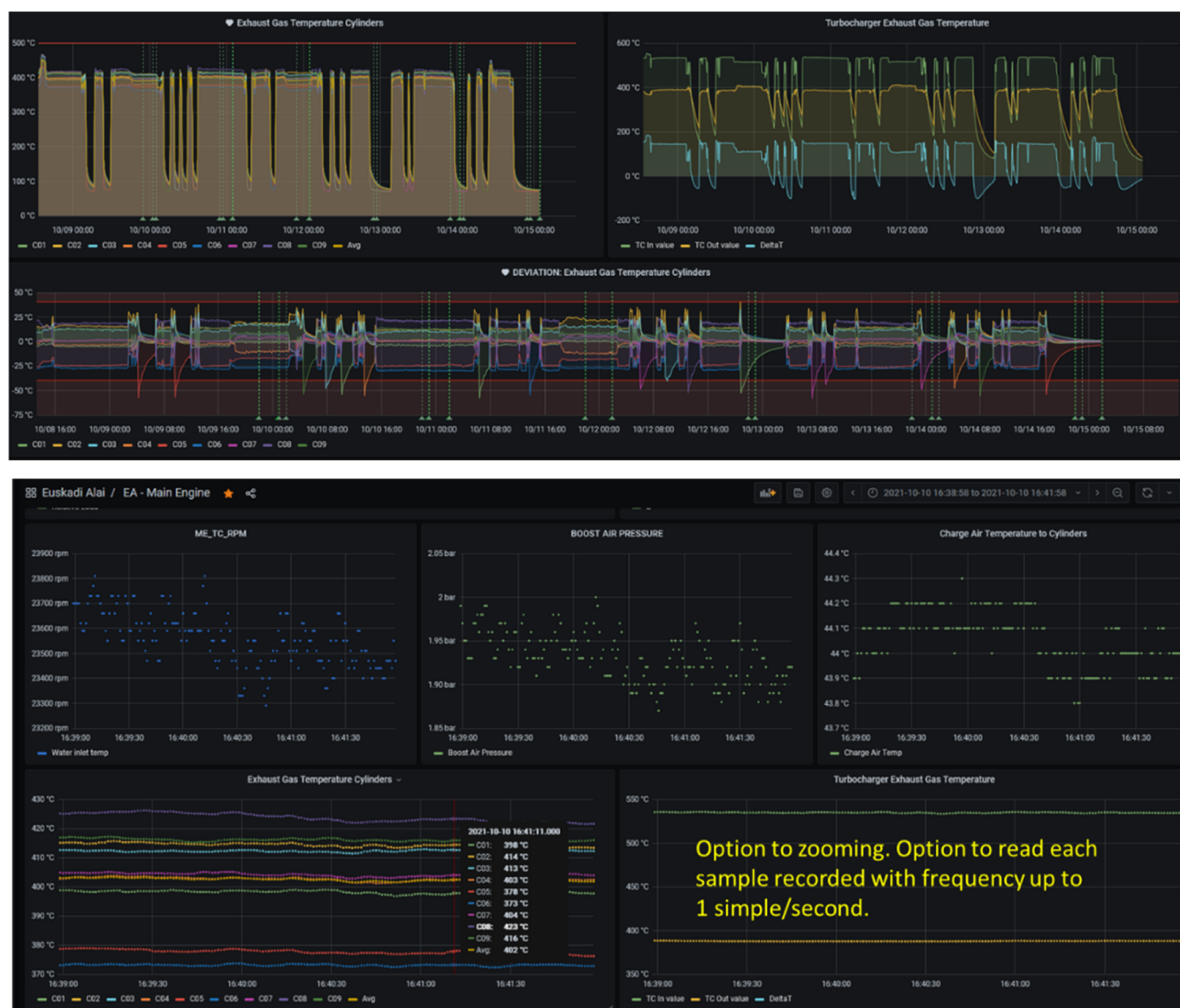
Figure 3. Example of Main Engine variable Dashboard on top panel and options to modify time window and zoom up to detailed parameter in the bottom panel.

based on the ISO 19030-2 (2016)[38] international standard. The propulsion variables are used for fuel consumption modeling and a condition-based maintenance program. The fuel oil consumption onboard a fishing vessel is distributed in propulsion load and auxiliary load onboard, i.e., the energy required to move the vessel and energy required to keep vessel systems in operation (mostly electricity load and hydraulic system load required to pump fluids). For the candidate vessels in this research, propulsion accounts for 70−75% of total energy consumption and auxiliary loads 25−30%. This distribution depended on the variability of fishing operations during the year.[39]

The Ratatosk framework[40] is used for integrating all sensors of interest. Ratatosk has been developed to facilitate simpler data integration and communication on fishing vessels. It can interface with relevant hardware systems and protocols, such as Canbus, Modbus, and NMEA, and new interfaces can be added as necessary. The interfaced sensors and systems are made available through the Ratatosk main communication bus for easy two-way communication. This facilitates easy vessel integration and simple reuse for future applications and extensions.

3. CANDIDATE VESSEL IMPLEMENTATION

Two commercial tuna fishing vessels acted as pilot vessels for development and demonstration. Figure 2 shows the systematic arrangement of the proposed holistic monitoring and energy management system. The installations of system components occurred mainly in the engine room (ER), the engine control room (ECR) and the wheelhouse (W/H). Data communication between the different locations and onboard vessel systems was primarily done over Ethernet (Figure 2). Two interconnected switches, located in the wheelhouse and in the engine control room, formed the backbone of the onboard data exchange network, through which the data sources communicate. Converters were used for interfacing systems and sensors unable to communicate over Ethernet, such as serial to Modbus-over-Ethernet converters. Distributed Ratatosk components could also perform this function, but converters were chosen for these vessels. The Ratatosk server acts as the central hub of the monitoring system. It provides the shared data space, records data to file, and sends them to shore. To this end, it is also connected to a managed switch,

Table 2. List of Variables Measured for Fuel Consumption Development[a]

variable	group	type	description	unit
ME_FO_consumption	ME	D	fuel oil consumption of main engine after density correction	l/h
AE_FO_consumption	ME	D	fuel oil consumption of auxiliary engines after density correction	l/h
Eng_Relative_load	ME	I	main engine relative load from 0 to 100%. 100% load = 4500 kW	%
FO_Rack_position	ME	I	fuel oil injection pump rack position. From 0 to 53 mm. It has a strong correlation with engine power	mm
engine_speed	ME	I	engine turning speed affecting propeller pitch	rpm
FO_demand	ME	I	fuel oil demand. Range is from 0 to 10 000 ppt. Maximum value corresponds to 100% load	ppt
propeller_pitch	PP	I	propeller blades position indication. Varies from 0 to 100%. The propeller is a controllable pitch propeller and can change pitch	%
torque	PP	D	torque in propeller shaft	kNm
propeller_shaft_rpm	PP	D	propeller shaft speed. It is used to calculate propeller output	rpm
propeller_shaft_output	PP	D	propeller shaft mechanical output (power)	kW
propeller_shaft_thrust	PP	D	thrust generated by the propeller in the shaft	kN
ME_FO_inlet_flow	ME	I	volumetric fuel flow inlet to the main engine. Used to calculate fuel oil consumption	l/min
ME_FO_outlet_flow	ME	I	volumetric fuel flow outlet from the main engine. Used to calculate fuel oil consumption	l/min
AE_FO_inlet_flow	AE	I	volumetric fuel flow inlet to the auxiliary engines. Used to calculate fuel oil consumption	l/min
AE_FO_outlet_flow	AE	I	volumetric fuel flow outlet from the auxiliary engines. Used to calculate fuel oil consumption	l/min
ME_FO_inlet_temp	ME	I	temperature of the fuel oil in the inlet of the main engine. Used to calculate mass flow rate in the inlet to the engine using fuel density	°C
ME_FO_outlet_temp	ME	I	temperature of the fuel oil in the outlet of the main engine. Used to calculate mass flow rate in the outlet from the engine using fuel density	°C
AE_FO_inlet_temp	AE	I	fuel oil temperature in the inlet of the auxiliary engine. Used to calculate mass flow rate in the inlet to the auxiliary engines using fuel density	°C
AE_FO_outlet_temp	AE	I	fuel oil temperature in the outlet of the auxiliary engine. Used to calculate mass flow rate in the outlet from the auxiliary engines using fuel density	°C
SOG	SH	D	vessel speed over ground from GPS signal	knot
STW	SH	D	vessel speed over water from the doppler system	knot
AE_Power_1	AE	I	electrical power generated by diesel generator #1	kW
AE_Power_2	AE	I	electrical power generated by diesel generator #2	kW
AE_Power_3	AE	I	electrical power generated by diesel generator #3	kW
AE_Power_4	AE	I	electrical power generated by diesel generator #4	kW
AE_Power_5	AE	I	electrical energy generated by diesel generator #5	kW
wind_velocity	WE	I	wind relative velocity to vessel	m/s
ship_wind_angle	WE	I	wind relative angle to ship	deg
draft_fore_side	WE	I	vessel draft in the fore side	m
draft_aft_side	WE	I	vessel draft in the aft side	m
ship_inclination	WE	I	ship inclination	deg
MRU	WE	I	ship angular velocity and acceleration	deg/s, s^2

[a]Abbreviations stand for: I: Indirect, D: Direct, ME: Main Engine, AE: Auxiliary Engine, PP: Propulsion, SH: Ship, and WE: Weather.

which gives periodic Internet access using the ship's VSAT system. The Ratatosk server sets up two secured and encrypted communication channels. One is for remote connection, and the other is for remote configuration.

The monitoring and energy management system was designed to incorporate existing sensing devices without data integration capabilities. This included: (1) the engine control system; (2) the propulsion efficiency monitoring system; (3) the ship power management system; (4) the fish hold cold storage system; and (5) the ship draft and inclination sensors.

The main engine includes manual monitoring operations, i.e., manual measurements of the engine parameters with specific tools. The most common method is the engine cylinder combustion pressure measurement. For a full system integration, an IMES combustion control module (CCM) was installed in the engine room. This system comprises one sensor for continuous combustion pressure measurement per cylinder, a pickup for RPM and cylinder position measurement, and a cylinder inlet pressure sensor. It outputs digital measurements to a controlling computer in the engine control room and as a CAN output. The latter is further converted to Modbus TCP by a dedicated converter for integration with Ratatosk. In

addition to receiving these instantaneous measurements, the Ratatosk receives engine combustion analyses and statistics from the engine control room computer. Two programmable logic controllers (PLCs) make approximately 110 measurements from various systems available over Modbus, in addition to some combustion measurements.

Since the diesel engine operational parameters are influenced by ambient conditions, a Delta OHM monitoring device measures ambient pressure, temperature, and relative humidity in the engine room. It outputs its measurements over the RS485 protocol, which a serial-to-ethernet converter relays to the monitoring network. A motion reference unit (MRU) is installed close to the ship center of gravity to measure the ship movements. It outputs over RS232, and a serial to Ethernet converter relays its measurements to the monitoring network through the switch in the engine room. Not all the sensors established by the ISO 19030 as minimum sensors were available onboard and were not possible to install for this research. Specifically, the rudder angle was not measured by the acquisition system.

4. SYSTEM MONITORING AND MAINTENANCE

Monitoring and maintenance is a central part of such a system, comprising a large number of subsystems susceptible to changes and faults. For this reason, automatic fault detection would be a natural part of the final system. To fulfill this role for the candidate vessels, a semiautomatic system has been developed. This is based on providing useful ways for checking and maintaining the system in an operative state through remote access and easy-to-interpret visualizations.

For visualization, the GRAFANA[41−43] visualization software is being used (Figure 3). This solution permits an easy visualization of all the monitored variables, which is especially helpful for the health check of the monitoring system and ensuring that reliable data is collected. It is necessary to remark that GRAFANA is being used for visualization (by the scientists at testing and the crew on operational time) rather than actual data analysis. Each monitoring subsystem has a dashboard: (1) anemometer; (2) auxiliary engine; (3) engine room ambient parameters (DELTAOHM); (4) Fish holds; (5) MarPrimeUltra; (6) Main engine; (7) Motion and MRU data; (8) Maxsea and GPA navigation data; and (9) fuel oil consumption and propeller shaft. By grouping dashboards into monitoring subsystems, it is easier to check the performance of the system. When data analysis is carried out, it is not possible to go backward in time, so it is necessary to have systems up to date (Figure 3).

The system facilitates remote system checking. The system provides a secure login to the Ratatosk server, enabling both monitoring of the signals on the Ratatosk bus and the health of the system. In addition, a remote desktop to the IMES computer can be enabled when necessary. In addition to being used for checking system health, this provides a means for doing remote maintenance when necessary. The configuration channel can be used in similar ways and is primarily concerned with keeping configurations updated, version controlled, and sound.

5. SYSTEM USAGE AND BENEFITS

The main engine in the candidate vessels is a medium speed 4 stroke diesel engine. According to the engine manufacturer, a well-planned condition-based maintenance program can draw fuel oil consumption and emission reductions between 2% and 5% and avoid unplanned stops from 60 to 90%. The fuel oil consumption reduction brings a direct reduction of GHG emissions; however, other pollutants are more complicated to estimate, as a diesel engine operating in bad conditions can emit more of other pollutants like NOx.[44] Therefore, other main engine parameters are also a very important group of parameters to be measured. The monitored combustion variables can be used to infer the several operational engine parameters using machine learning techniques.[45] As part of the vessel digitalization process, Artificial intelligence (AI) techniques will potentially be used to develop a condition-based maintenance model in the future. Until now, many authors have proved the feasibility of using AI techniques in their studies,[46−49] but implementation of the outcomes from these studies requires a vessel digitalization platform.

Measurements on the main engine, propulsion system, and auxiliary engines are needed to develop the fuel oil consumption model. In this research, up to 140 parameters from the main engine (Table 2) were considered for monitoring. Vessel and environmental variables are measured

to include the environmental impact on vessel fuel oil consumption. Main engine measurements also support the development of fault detection models for condition-based maintenance. These measurements can be divided into direct and indirect measurements. The direct measurements measure the energy consumption (i.e., fuel oil consumption with flow meters), while indirect measurements can be used for calculating energy consumption (i.e., fuel injection pump index position). The indirect measurements often constitute a redundancy in the case of failure on the direct measurements, such as faulty sensors. As an example, fuel oil consumption could be calculated from measurements of the fuel injection pump index position and engine RPM.

The fuel oil consumption is measured by volumetric flow meters, measuring the fuel flow to and from the engine. However, the energy content in the fuel is proportional to its mass. If the difference in fuel flows is directly used without density correction, this would give an estimated error of 2−3%. The volumetric flows are therefore corrected based on measurements of inlet and outlet temperatures for each engine. Each engine inlet volumetric flow, inlet temperature, outlet volumetric flow, and outlet temperature must be measured to calculate the consumed fuel mass flow. The instantaneous propulsion power is calculated from measurements of the propeller shaft torque and rotational speed. The fuel oil consumption and the generated electrical power of the auxiliary engines are measured. The vessels' electrical hotel load (electric power consumption) can then be found as the difference between the auxiliary engines' electrical power and the sum of any major consumers not considered to be part of the hotel load. Vessel speed is measured in terms of both speed over ground and speed through water. Speed over ground is provided by the GPS, while speed through water is measured from the speed of the water flow under the hull. The combination of these measurements, as well as the ship heading and the course over ground, gives additional information about the ship environment and makes it possible to estimate current effects. These effects are important and must be considered when modeling the vessel energy consumption. Vessel speed through water is considered as more accurate value for fuel oil consumption modeling (ISO/CD 19030-1, 2017).[50] Vessel environmental conditions (wind speed and direction) are also measured, as well as vessel draft, trim, and inclination. Vessel accelerations and motion are measured with an inertial motion unit (IMU) that provides many different motion variables (angular acceleration and angular speed).

6. CONCLUDING DISCUSSION

Despite the growth in the capacity to collect, store, and analyze data has increased,[51] cost-effective data collection with industry for integration with scientific data from oceanographic surveys is sparse.[52,53] Besides, it is estimated that 80% of research time is consumed in data preparation, which is why it is important to digitalize the vessels and build repositories with interoperable and reusable data.[54,55] Large data sets analysis and application development in the bioeconomy sector can be accelerated by recent providers of Big Data, such as the Copernicus initiative and its Sentinel satellites for EO.[56]

The vessels participating in this study are operating as data collection platforms and as consumers of data from AI and big data systems. This work goes beyond previous work that has demonstrated the deployment of decision support systems in

four commercial vessels without modifications.[40] Some of these data sets can be classified as Essential Ocean Variables (EOV), defined by the Global Ocean Observing System (GOOS) experts as those who are effective to contribute to deal with the Climate, Operational Ocean Services, and Ocean Health.[57,58] Besides EOV available in ocean data repositories or aggregators, current data are being collected operationally in Vessels of Opportunity (VoOs) or Voluntary Observing Vessels (VOS). For example, the scheme coordinated by the World Meteorological Organization has approximately 2000 vessels participating and acting globally as remote weather stations. The near-surface observations taken include atmospheric pressure, wind speed and direction, air temperature, relative humidity, and sea surface temperature (SST), as well as wave height, direction, and period. The value of these data is recognized in Regulation 5, "Meteorological Forecasts and Warnings", of the Safety of Life at Sea Convention (International Maritime Organization [IMO], 2002), which encourages contracting governments to arrange for a selection of ships to be equipped with tested marine meteorological instruments and to take, record, and transmit meteorological observations at the main standard times for surface synoptic observations. The Continuous Plankton Recorder is another example aimed at biological information gathering.[59,60]

This work facilitates that data is useful and manageable according to the Findable, Accessible, Interoperable, and Reusable (FAIR) principles, which were created with the aim of being a guide for improving data accessibility and reuse.[61,62] However, other principles also need to be considered. CARE principles were created with the aim of providing more control over the use and application of data.[63] FAIR focuses on making the data accessible and reusable, whereas CARE aims to use the data for purposes beyond dealing with numbers and, in the case of sensitive information, always with the group or population in mind. Finally, TRUST principles aim to create trustworthy repositories.[64] Despite the presented example here focus on fishing vessels (use of the same devices and protocols), the digitalization and FAIR data approaches can also be applied to the shipping industry. The shipping industry can become producers of not only environmental but also biological data.[59]

The proposed monitoring system provides the needed data for cost-effective data provision for forecasting systems needed for decarbonization of the industry. For example, machine learning models can create accurate engine models that are able to predict the engine parameters under different operational conditions with enough accuracy to be used as reference values to compare with actual operational parameters.[65] Deviations from predicted parameters prior to fault occurrence can help the crew to proactively operate the engine and solve engine malfunction accordingly before occurring a catastrophic fault that can endanger vessel and crew operation.[66] As some authors have clearly stated, if more efficient ship operations are to be defined, energy consumption in the full operational profile of the vessel is completely necessary.[67] The fuel consumption models can predict fuel oil consumption in autonomous mode. This will also permit specialization of staff on shore in energy efficiency areas, creating an energy efficiency culture in vessel operation. All of this increases vessel safety, reduces vessel downtimes and fuel oil consumption, and increases vessel economical sustainability.

Actually, the collected data is feeding fuel prediction models,[68−70] species distribution models, and route optimization models[71] being used by the vessels participating in this work. The fuel prediction models based on AI methods[68] are being used to estimate the optimal speeds and current fuel consumption as well as feed into route optimization models.[71] These models combine large data sets of fuel consumption recorded from the vessels with large environmental data sets from Copernicus (Figure 4). Similarly, species distribution forecasts based on artificial intelligence methods using Copernicus data are being provided to the vessels and used for route optimization.[71]
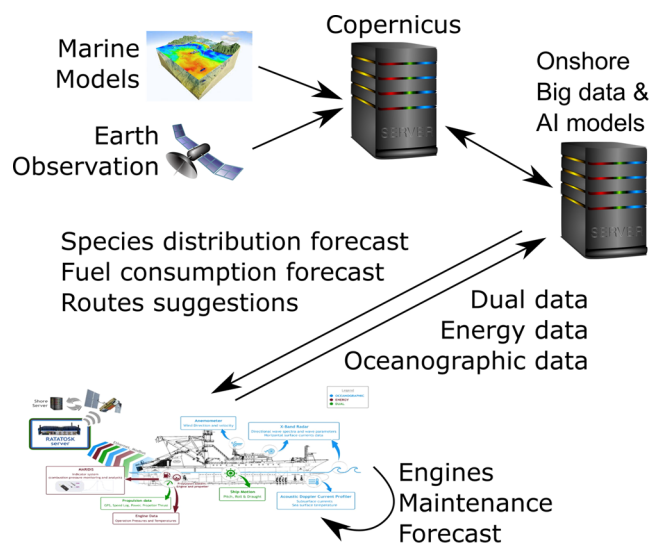
Figure 4. Data flows of the in situ data from the vessels to Onshore vessels and the returning forecasts to the vessels for improved operations.

Furthermore, the integration of such models in international data platforms will help to forecast threads to the fisheries industry such as climate change.[6] This work aims to support scientists, industry, and policymakers in the understanding of the needed technological development for cost-effective data acquisition through fishing vessel digitalization. This digitalization is needed to facilitate the reduction of emissions as a critical environmental problem and industry costs critical for industry economic sustainability. In addition to data recording, this system facilitates the deployment of standardized two-way interfaces to onboard sensors and systems. This can remove a significant obstacle toward the development and deployment of applications based on interfacing ship systems. It would enable the development of monitoring systems and decision support systems without tailoring to each individual ship, which today is hindering the widespread use of such systems.

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Notes

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