

# Data Driven Fleet Monitoring and Circular Economy

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**Abstract**— The maritime industry is intensively embracing green thinking. According to the International Maritime Organization’s (IMO) Greenhouse Gas (GHG ) strategy, the total annual GHG emissions from international shipping should be reduced by at least 50% by 2050 compared to 2008. Shipping adopts policies to comply with the set target, including ship re-design, structural retrofit, use of low-carbon material, and the installation of emission abatement technologies. All these approaches pave the way to circularity in the maritime economy, abandoning the linear model in vessel lifetime and adopting lean management, re-manufacturing, and re-usability of the asset. To this end, in the SmartShip project, we give prominence to data-driven ship monitoring by delivering an Information and Communication Technology (ICT) & Internet of Things (IoT)-enabled holistic cloud-based maritime performance and monitoring system. This system is considering the entire lifecycle of a ship, aiming to optimize energy efficiency, emissions reduction, fuel consumption, while, at the same time, include circular economy concepts in the maritime field. Our approach supports a cost-effective strategy where data analysis drives decisions in ship operation and maintenance.

**Keywords**— Fleet management, IoT, Circular Economy, Lean management, Green Shipping, Life Cycle Assessment, Life Cycle Performance Assessment, Emissions, Energy, Maritime, IMO, GHG, Optimization, SmartShip, data analytics, DSS

## I. INTRODUCTION

SmartShip aims at utilizing knowledge exchange between academic and non-academic entities to realize a holistic framework aimed at analyzing key causal factors. The factors

mentioned can be summed in affecting energy efficiency and fuel consumption management, environmental compliance with the maritime sector regulations in terms of emissions control, and exploitation of technologies used for the aforementioned purposes. Whilst, most importantly, SmartShip’s novelty relies in the consideration of applications of circular economy concepts in the maritime field as an indivisible aspect of its objectives. Essentially, the project’s vital aim is to create an ICT framework for the sustainable, individualized and completely automated energy management of ships, offering a multi-layer optimization in the fields of fuel consumption, energy efficiency and emissions control while complying with the maritime sector regulations and requirements. To illustrate the aforementioned objective our research focus is laying on the integration of existing tolls with a variety of implemented and validated new technologies, within the project’s framework. Integration will lead us to data driven fleet monitoring ecosystem which targets at optimizing the efficiency of daily operations (e.g., via weather routing optimization, trim optimization, real-time optimal navigational adjustment, vessel’s performance under voyage scenarios and ship settings and real-time detection of complex events). The final product of this research will be

- A fully developed data analytics and decision support tool, which will compile data from existing sensing devices in vessels, manage the operation of the whole IoT environment, and run optimization algorithms to provide suggestions related to the maintenance of the ship machinery and hull as well as the vessel operation.

- This data-driven modelling of fleet operation and performance monitoring is a cost-effective solution to reach green and sustainable shipping operation against the conventional approach that relies solely on cost intensive state-of-the-art traditional solutions like hardware installation, fuel alternatives and retrofitting.

SmartShip framework supplements traditional approaches to limit the necessity of huge capital expenditures from the asset owners while following a circular design where fleet utilization is optimized, ship lifetime is prolonged through a sustainable operation, data is reused and further exploited while decision making is value driven. To achieve project research goal, SmartShip targets to foster knowledge exchange between experts of complementary technology fields (IoT, Data Analytics, Visualization Tools, Optimization Algorithms) and circular economy designers towards the development of a holistic and sustainable framework for energy efficiency and emissions control, thus materializing the next-generation paradigm for the maritime industry.

The rest of the paper is structured as follows. The next section reviews related technologies and work that foster the development of the SmartShip framework. Then, Section III describes the transition from a linear to a circular economy. Section IV delivers insights over SmartShip methodology and architecture and concludes with a description of how the SmartShip framework meets circular economy principals in Section V.

## II. RELATED WORK

SmartShip takes advantage of state-of-the-art tools and frameworks to build and develop the project's holistic solution by researching the fields of (i) Energy efficiency management and monitoring and emissions control in the maritime; (ii) Cloud-based and IoT Systems use in Maritime; (iii) Sensors' technologies in Maritime; (iv) Algorithms and optimization technologies (e.g. Life Cycle Assessment, LCA) in Maritime; (v) Advanced data analytics, and decision support systems and (vi) Circular Economy as applicable to Maritime. Throughout thorough research of the aforementioned fields, a comprehensive utilization of the existing tools in the market has been implemented, to facilitate the process of developing the project's solution, which builds upon the presented tools.

Regarding the energy efficiency optimization tools, which aid in energy efficiency management on vessels, a tool developed by the International Maritime Organization (IMO), the Ship Energy Efficiency Management Plan (SEEMP) has been developed to properly measure and control GHG emissions from the existing fleets. The main objective of SEEMP is to reduce GHG emission while increasing operational efficiency of the ship resulting in less fuel consumption. Speed optimization, Weather routing, Hull monitoring and maintenance, Efficient cargo operation and Electric power management are taken into consideration to achieve efficient operation, among others [2]. Consequently, Emission Control Optimization employs multiple factors throughout the vessels' life cycle to estimate emissions and thus optimize their levels; the aforementioned factors are actualized in (i) fleet dynamics (fleet renewal, size increase), (ii) fuel consumption, and (iii) emission factors. Fleet dynamics are crucial, for ships of different sizes have different emissions profiles [3]. Fleet dynamics include the rate of fleet renewal and the increase of size, which is based on the EU-active fleet in the last 5 years. An example of projects aiming

to precisely estimate the calculation of fleet renewal rates is the EMMOSS project, where survival functions were estimated from the United Nations Conference on Trade and Development (UNCTAD) annual maritime review to achieve that calculation [4]. For Fuel Consumption, a calculation can be performed using the required energy of the vessel and its efficiency, where operational speed is important, and its relationship with propulsion energy is defined by propeller law. This means that the required propulsion energy is not linearly proportional to vessel speed. From the vessel data, one can estimate the operational speed and installed (propulsion and auxiliary) power of the different ship types. Thus, the determination of the required propulsion energy/km is possible, given an assumption on the percentage of installed power used at cruising speed; while in the literature, a ratio of 75-85% is common [5][6], recent empirical evidence suggests a lower estimate [7].

Regarding Technologies, SmartShip takes advantage of existing hardware and software to present a total framework for energy efficiency management, creating a framework that combines data analytics and IoT tools that have already been used in the Maritime sector. Where IoT is present in a multitude of domains, in Maritime, it provides all-inclusive monitoring and control to the crew of any ship to drastically enhance management through the usage of sensors and unified platforms. The use of IoT in the maritime domain aims to prevent unpredicted downtime, energy efficiency monitoring, reduction in maintenance costs and complex event detection or trajectory classification.

In general, classification techniques aim to identify complex events in the trajectories by extracting features that are capable of distinguishing patterns in their movement [8]. There are several techniques for trajectory classification that extract different trajectory features used as input for classifiers. The main difference between the classification techniques is the type of features they extract for training the classification model [9]. Most works in trajectory classification extract features from the spatio-temporal properties of trajectories such as speed, acceleration, and direction change. Bolbol [10] segments trajectories in a pre-defined number of sub-trajectories and using a sliding window. The method extracts features such as the average acceleration and average speed. Soleymani [11] segments the trajectories by using two types of grids. The first grid splits the trajectories based on their spatial location, and the second grid divides the trajectory by using a time window. This technique calculates features such as the standard deviation of speed and maximum turning angle from each sub-trajectory inside a grid cell. Dabiri [12] calculates four features from sequential trajectory points (speed, acceleration, direction change and stop rate) and represents the trajectories as a vector of four dimensions, where each vector dimension is the sequence of a given feature value. Dodge in [13] calculates the features of speed, acceleration and direction change between every two consecutive trajectory points while Xiao [14] and Etamad [15] extract several statistics from trajectory points such as the percentiles, interquartile range, skewness, coefficient of variation and kurtosis from the speed, acceleration, and heading change.

Nevertheless, only in recent years, researchers shifted focus towards the maritime domain, and as a consequence new research challenges emerged [16], [17], [18], [19]. Three different classifiers, namely trawlers, longliners, and purse

seiners are employed for the detection of different fishing vessel activities in [20]. In [21] autoencoders are proposed for fishing activities detection based on transmitted AIS messages. The DBSCAN algorithm is performed for Points Of Interest (POI) extraction in fishing vessel trajectories to create features used for the training of a classification model. In [23], a combination of General Hidden Markov Models (GHMMs) and Structural Hidden Markov Models (SHMMs) with a Genetic Algorithm (GA) are utilized for trajectory classification. Additionally, neural networks are widely used for trajectory classification. Jiang et al. [24] employed Recurrent Neural Networks (RNNs) for point-based trajectory classification into four different transportation modes. In [25], a deep multi-scale learning model was used to model grid data under different space and time granularities, thus capturing the impact of space and time on the classification results. Furthermore, a novel partition-wise Gated Recurrent Unit (pGRU) architecture is employed in [26] for point-based trajectory classification on detecting trawler fishing activities. Finally, a universal deep learning multi-class streaming classification methodology for trajectory classification is presented in [27].

The specific technologies that usually materialize this scope include a variety of monitoring/sensing and actuating equipment such as Radio-frequency identification (RFID) readers, sensors, actuators, cameras, and GPS. Ericson™, for instance, designed a holistic Maritime ICT cloud system, which aims to better connect vessels at sea with shore-based operations, maintenance service providers, customer support centers, fleet/transportation partners, port operations, and authorities [28]. In addition, it is expected that such a combined framework of Big Data Analytics and IoT can help obtaining real-time analytics results to support vessel operations; analytics results to support the diagnosis of vessels, predictive maintenance, and allocation of maintenance facilities and resources, especially for offshore service vessels (OSVs) operating in different international locations due to globalization; (3) analytics results on operation challenges in different waters and weather situations to facilitate and prioritize new components and designs. Also, from a regulatory perspective, BDA on sensor-enabled operation data can improve energy efficiency and environmental performance, safety verification and assessment, and the monitoring of accidents and environmental risks, and help regulators introduce more quantified regulations for the administration of ships and seas [29].

### III. LINEAR VS CIRCULAR ECONOMY

Jørgensen, and Pedersen express in their paper that the “future goes in circles”, while explaining the basic concepts of circular economy and the multitude of benefits the concept provides to the economy [30]. In contrast to what the conventional “linear approach” demonstrates in merely manufacturing, consumption, and waste of products, the circular approach gives the raw materials used in creating vessels another chance of being useful; the materials used can be utilized in three main approaches: balancing the usage of possibly-depleted materials such as metals and minerals that are finite, designing products with parts that can be reused or reassembled to cut down the waste of scarce resources, which facilitates the process of upcycling, and maintaining the products and materials within their life cycle at the highest quality possible to ensure long-lasting durability of the

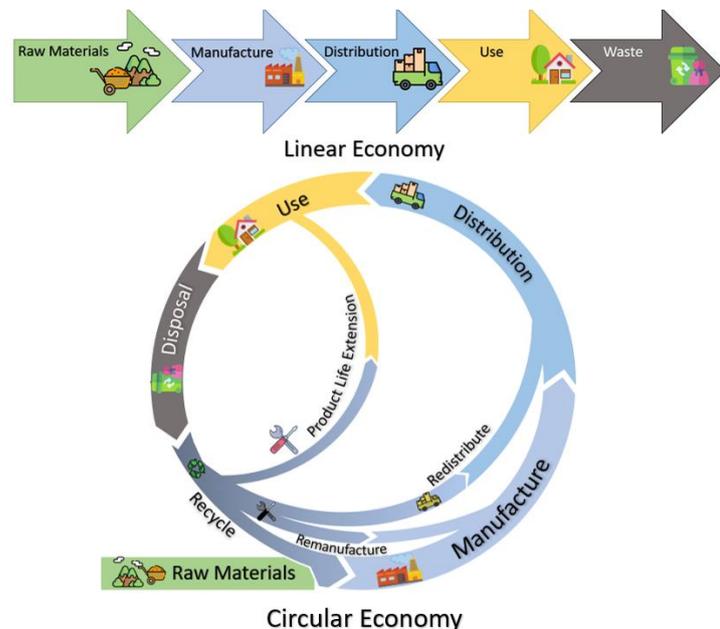


Figure 1 Linear Vs Circular Economy

products. A comparison between linear and circular economy can be observed in Figure 1, Linear vs Circular Economy. In a nutshell, the best way to define a circular economy is presented by the Ellen MacArthur Foundation [31], which defines circular economy as an industrial economy that is restorative by intention, which aims to enable effective flows of materials, energy, labor, and information so that natural and social capital can be rebuilt. At the same time, the circular economy aims to minimize energy consumption use per unit of output and accelerate the shift to renewable energy by design; thus, it considers every resource available in the economy valuable and indispensable. The final objective presented by the foundation regarding the concept is an economy that sustains the value of its products, materials, and resources for as long as possible, while at the same time minimizes the generation of waste through reusing, repairing, refurbishing, and recycling existing materials and products [32].

## IV. METHODOLOGY

### A. Architecture of Solution

SmartShip main aim is to develop a holistic framework for energy efficiency and emissions control incorporating technological advancements, information harvesting, short/mid-term decision support tools and human intellect, thus materializing the next-generation paradigm for the maritime industry. This aim will be realized by deploying an architectural design that contains 5 main components, integrated to deliver a state-of-the-art solution (Figure 2 SmartShip Architecture). Mainly, the solution’s framework is comprised of the following components:

- **The IoT backbone:** This component will be based on (i) existing, already installed sensing devices in vessels that gather several types of information related to a) the operation of the engines and the environment (emissions level, fuel consumption, engines’ fatigue, engine components’ status, energy consumption etc.), and b) to

the vessel's behavior (speed, draught, location and rate of turn) that are transmitted through the Automatic Identification System (AIS) on board the vessel; (ii) any other external data that may be exploited by the data analytics and the decision support modules (such as

pollution or increased emissions, enabling proactive action.

- **The Optimization Algorithms:** The algorithms are based on data gathered from the IoT backbone and the analysis carried out in the data analytics module. Specific

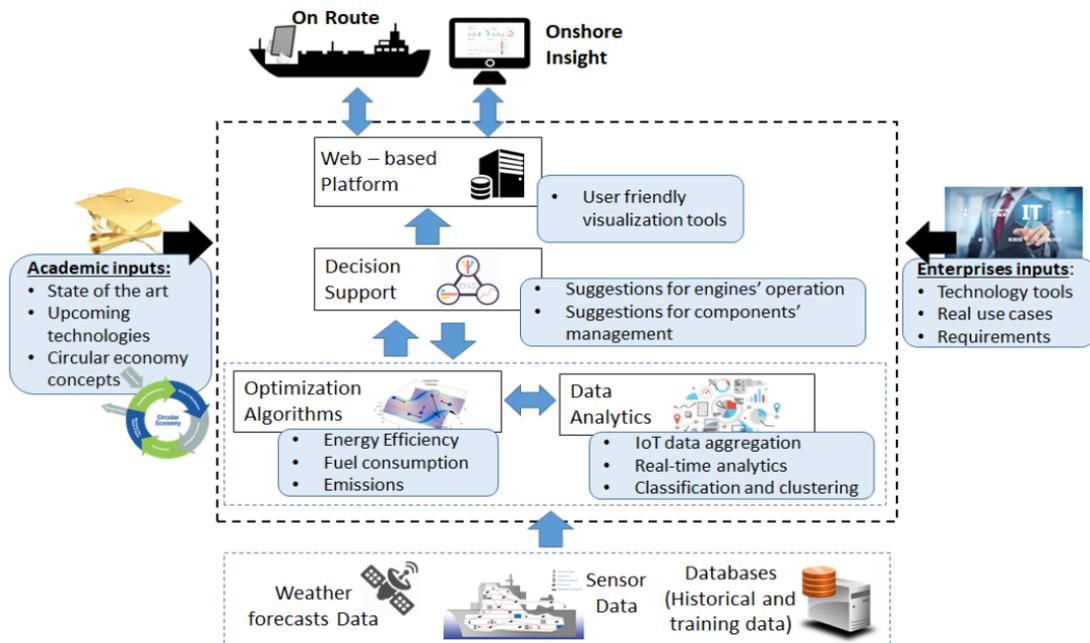


Figure 2 SmartShip's Architecture (SmartShip, 2020)

weather forecasts), and (iii) historical data stored in databases, related to previous operations and decisions of the system in specific contexts.

- **The Data Analytics Module:** This component will be responsible for aggregating data and analyzing it in real-time. Also, based upon a source agnostic interoperable IoT framework with the capacity to harvest vast amounts of data available in a network of interconnected sensors. The input data utilized (e.g., fuel/energy consumption, emissions, modules' performance, operational and environmental conditions, vessel's behavior) will be processed, refined, and analyzed, respectively. Consequently, the obtained information from the analysis will continuously feed and update a deep-neural predictive model of the vessel, allowing the evaluation of the vessel's performance under different voyage scenarios and vessel settings. Furthermore, the high-frequency and large volume data associated with vessels' operations and behavior will be further compressed with as minimal information loss as possible. Most vessel movements on the water are relatively steady in space; thus, the shape of a vessel trajectory can be represented by only a small portion of carefully selected points. Trajectory compression aims at substantial reductions in the amount of data while preserving the quality of information, and thus ensuring the accuracy of the trajectory. As a result, real-time detection of complex events with low latency and high throughput (e.g., identifying that in the current weather conditions, a reduction in engine power improves energy efficiency) will result from this process. Finally, collected data will be utilized in predicting malfunctions that may cause

optimization algorithms will be tested and applied, focusing on a multi-layer optimization that comprises (i) energy efficiency maximization; (ii) emissions minimization and (iii) fuel consumption minimization. An additional factor that will be used in these algorithms refers to the overall Life Cycle of engines' components, focusing on circular economy – based guidelines/perspectives as data – particularly big data – is circular by nature.

- **The Decision Support Module:** This module provides suggestions for strategic mid/long-term decisions, connected to incorporated novel energy efficiency and emissions control technologies and for the engines' components management. This toolset includes trim optimization and optimal weather routing, whilst incorporating various aspects of waterborne navigation, such as anisotropic areas, environmentally sensitive regions, and weather conditions. Further, it includes an expert system that suggests course and engine power readjustments in real-time for optimal energy consumption. The tools will utilize the deep-neural vessel model which allows assessing the ship's performance correlated with the given weather and operational conditions. In addition, circular economy aspects are taken into consideration; SmartShip offers lifecycle management and assessment tools (Life Cycle Assessment (LCA) , Life Cycle Performance Assessment (LCPA) for the evaluation of innovations with respect to their productive energy efficiency, considering market/financial data in conjunction with the current and the optimal operational performance of the vessel [35].

- **The Cloud-Based Platform and interoperable IoT/ICT framework:** A fully integrated ICT/IoT framework for the maritime industry requires homogenizing a complex interconnected network of sensors and actuators, while handling compression and cyber security issues for satellite communication and offering gateways to the company’s enterprise systems. A standardized semantics scheme will be the basis of this interplay. A cloud-based platform will host the SmartShip tools and services, accommodating the related high-frequency, voluminous data and computational needs. An integrated dashboard (“DashOnBoard”) with advanced visualization tools will act as the single point of interaction of the user with the incorporated systems, services, and tools, e.g., supporting decision making of the navigational officer (Captain Tips), of the center of operations at shore (Company Tips) and of the various other stakeholders (Custom Tips).

## V. REALIZING CIRCULAR ECONOMY

Utilizing the shared knowledge between academic and non-academic consortium partners, SmartShip novel approach is to couple the use of Circular Economy and Smart ICT-enhanced maritime fleet management and provide fertile ground for innovation and value creation. As explained in the previous section Linear vs. Circular Economy, Circular economy value drivers include extending the useful life of finite resources and maximizing the utilization of assets, thus creating an emerging class of “intelligent assets” and regenerating natural capital for more effective and efficient use [33]. ICT-enhanced infrastructure can facilitate this by collating knowledge on asset locations, conditions, quality, and performance in real-time and overtime. ICT and smart assets in specific are already presenting solutions to many resource challenges faced by circular economy innovators. The feedback-rich nature of circular economy models might conversely make them particularly suitable to help extract value from the large amount of data generated by smart maritime assets. A broad range of opportunities emerges when these value drivers are paired. Ship and fleet operating efficiencies are multifaceted and interdependent; as such, efficiency management must involve an integrated solution that extends across the entire operation of the fleet [34]. No single metric can be used to indicate success or failure of improving overall efficiency. Rather, comparative analysis of multiple metrics is required. Furthermore, to be viable, efficiency management must accommodate operating priorities, goals, and constraints. Technology to save fuel and reduce carbon footprint is only useful if critical mission objectives are also met. It is evident that during the last years, enormous research effort has taken place towards accurate energy and emissions monitoring, modelling and management in the maritime sector. In this overall effort, SmartShip aims to provide a complete framework that will take advantage of all possible technologies and methodologies to provide a complete and applicable energy efficiency management.

SmartShip aims at reaching a circular economy through an innovative solution that increases energy efficiency, optimizing fuel consumption, and emission optimization. The solution is regarded as innovative throughout its utilization of data analytics, decision support systems, and the incorporation of Circular Economy principles in vessel management.

Regarding the autonomy level of SmartShip, which is based on advanced data analytics and decision support, SmartShip foresees a system that will empower ship systems and engines to autonomously adjust their operation based on several requirements and a plethora of data sources, to achieve optimization in terms of fuel consumption, energy efficiency, and emissions. Towards this direction, the integration of innovative technologies in terms of data analytics, decision support, real-time optimization as well as visualization will be investigated both in terms of literature and existing tools. On the other hand, employing the concepts of Circular Economy in vessel management is actualized throughout SmartShip end solution. Energy efficiency, fuel consumption and emissions optimization will be combined with data related to the Life Cycle of engines’ components (whose operation significantly affects the optimization in the aforementioned fields) to ensure that the overall management of these components is based on the main principles and guidelines related to Circular Economy.

## VI. CONCLUSION

Global efforts in the maritime sector have been redirected into switching to sustainable, environmental-friendly approaches. Rather than the conventional linear approach: take, produce, consume, and dispose-off, the circular economy gives vessels another chance to be reintroduced to the market either as spare parts or as a repaired product. Following that approach, raw materials will be less utilized reducing the GHG emissions that negatively impact the environment, while maritime enterprises can reduce the costs of procuring vessels and tools. Ultimately, the goal of SmartShip is to develop a framework that employs the adoption of lean management, re-manufacturing, and re-usability of the asset throughout the usage of ICT and IoT-enabled holistic cloud-based maritime performance and monitoring system. The system developed throughout the life cycle of the project is meant to optimize energy efficiency, reduce emissions from vessels, reduce fuel consumption, while implementing circular economy concepts in the maritime field. The final solution of SmartShip will be a fully developed data analytics and decision support tool that will be employing data gathered from IoT sensors currently available aboard vessels, run optimization algorithms that provide recommendations on operations in the ship’s machinery and manage holistic IoT environment operations. The project architecture will be comprising the IoT Backbone, the Data Analytics Module, the Optimization algorithms, the Decision Support Module, and the Cloud-Based platform and Interoperable IoT/ ICT Framework. Consequently, SmartShip will be building upon already-existing tools (COTS) and tools used by the consortium to further optimize their algorithms and features, thus complying with the circular economy towards the digital and green transition.

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