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Highlights

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- Agent-based model by integrating Bass diffusion theory and social network.
- First adoption model in eco-innovations that includes more than one technology.
- Model is fed with real data from pilot ships having three wind eco-technologies.
- Variation in adoption sensitive to installation price and potential fuel savings.
- Alternative business models to be implemented along the diffusion stages of WPT.

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Adopting different wind-assisted ship propulsion technologies as fleet retrofit: An agent-based modeling approach☆

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ABSTRACT

The maritime shipping industry will increasingly switch to low carbon fuels and adopt energy saving technologies (ESTs) to achieve the industry target of decarbonization. Among ESTs, deck equipment, including those based on wind propulsion technologies (WPTs), represents the largest potential fuel savings and a source of increasing innovation initiatives by industry actors. Previous contributions to WPT innovation have addressed barriers and drivers for increased adoption in the industry but failed to consider the specific aspects of the fleet retrofitting market. Through an agent-based simulation model, this work studies the effects of different policy and market scenarios (subsidies, fuel prices, and networking) on the adoption of WPT retrofitting solutions. The proposed model incorporates two decision steps for each vessel to adopt the technology (acquiring awareness of the technology, and a utility decision process to determine the WPT option). The study also expands on previous knowledge by modeling three WPT options and by integrating real world data of technology costs and their fuel savings as well as vessel features. Insights from simulations allow to identify the most convenient policies as well as the potential of alternative models to reduce introduction barriers (e.g., product-service business models).

1. Introduction

The maritime industry is a major contributor to global warming. It is responsible for 2.4% of global CO_2 emissions, with the transportation sector in general accounting for 24% of total CO_2 emissions (Clarksons Research, 2022a). The International Maritime Organization (IMO) aims to reduce greenhouse gas emissions by 50% compared to 2008 levels before 2050 (IMO, 2022). To reach this goal, the IMO policy initiatives rely on technological measures (installation of on-board green technologies), operational measures (improving ship operations through speed or route optimization) and market-based measures (such as emissions trading schemes) (Metzger, 2022; Nyanya et al., 2021). In this regard, relevant policy measures include employment of the Energy Efficiency Design Index (EEDI) and the Energy Efficiency eXisting ship Index (EEXI). In addition, the European Council and the European Parliament will negotiate in 2022 the inclusion of shipping as part of the EU ETS directive (Clarksons Research, 2022a). The IMO introduced energy efficiency regulations on 1st January 2013, and mandatory fuel records and reports of oil consumption for all ships above 5000 gross tonnage (GT) on 1st March 2018 through the MARPOL Annex VI (Lu and Ringsberg, 2020). The EEDI is the most important measure to tackle CO_2 emissions from shipping, requiring new ship builds after 2013 to implement carbon reduction technical measures (Rehmatulla et al., 2017). The EEDI was expanded in 2021 (MEPC 76) to include all ships above 5000 GT to calculate their EEXI, compared to the previous requirement of only ships built after 2013. From 2023, ships larger than 5000 GT will also be required to deliver annual reports on their carbon intensity indicator (CII) (Lindstad et al., 2022b). The CII works as a rating scheme measuring efficiency over time. A low rating in the scheme triggers correction requirements through an action plan such as the ship energy efficiency management plan (SEEMP) (Rehmatulla et al., 2017).

Cleaner shipping encompasses seaborne transportation stakeholders' strategies to comply with international commitments to reduce

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carbon footprints and emissions from their operations. Historically, petroleum derivates are the primary fuel for internal combustion engines on board ships (Prussi et al., 2021). Notwithstanding, recent literature pays attention to the technological developments around "alternative" (Prussi et al., 2021), "low- and zero-carbon (LoZeC)" (Bach et al., 2021, 2020), or "greener" (Lindstad et al., 2022a) fuels. A general categorization stems from the potential of the fuel to generate greenhouse gas emissions (GHG) well-to-tank and well-to-propeller compared to fossil fuels (Prussi et al., 2021). However, a more appropriate categorization of power sources for marine propulsion includes conventional fuel-consuming prime movers (gas turbines, internal combustion engines, steam turbines with boilers and fuel cells), radioactive fuel-consuming propulsion (nuclear-powered ships), and no fuel-consuming (photovoltaic, wind-assisted and battery electric ships) (Xing et al., 2021). In recent years, several alternative fuels have attracted the attention of researchers and shipping companies. Biofuels and liquefied biogas (LBG) are low-carbon fuels used in existing internal combustion technology on board ships. Biofuels require fewer changes in bunkering infrastructure and propulsion technology, given the capacity to recombine with marine diesel oil (MDO) or marine gas oil (MGO) (Bach et al., 2021). Liquefied natural gas (LNG) also fits within the low-carbon emissions category as it releases lower emissions of GHG in comparison to MDO or MGO. As a result, public policy often endorses LNG as part of sustainable shipping support programs, as in Norway (Bach et al., 2021). Hydrogen and ammonia are also examples of low-carbon fuel alternatives. Nevertheless, technically, they represent energy carriers as hydrogen, and ammonia production requires power from renewable sources or fossil sources (Bach et al., 2020). Furthermore, in shipping, hydrogen and ammonia propulsion is in the early maturity stages as regulatory developments are in progress, and bunkering and onboard storage issues are still challenging (Xing et al., 2021).

Wind-assisted shipping propulsion technologies, hereinafter referred to as wind propulsion technologies or WPTs, comprise a possible technical alternative for the decarbonization of shipping as a complementary propulsion by batteries (Thies and Ringsberg, 2022) or fossil fuel propulsion systems (Lindstad et al., 2022a). To date, the adoption of technologies of this type has been driven by niche developers, with a number of early stage adopters promoting the spread of knowledge about the different WPTs (Chou et al., 2021). Although WPTs do not constitute a breakout innovation for shipping, the new adaptations that complement conventional propulsion engines require extensive research and an understanding of how these technologies serve the heterogeneous needs of shipping customers, ship types and operating conditions. Such knowledge and understanding of user adoption requirements is necessary for diffusion to a larger market (Karslen et al., 2019). Retrofitting older ships is being portrayed as a viable option to integrating WPTs in new ship builds given the construction costs and the risk that WPT ships do not work as expected (Ballini et al., 2017). Vessels built between 2010 and 2014 represent 29% of global fleet tonnage, which represents a market potential for retrofitting with energy saving technologies such as wind-assisted propulsion or other types of energy conversion (Clarksons Research, 2022a).

Considering the global fleet green retrofitting market potential, knowledge about the market size of WPT as a retrofitting solution is still unclear. Several studies have pointed out the important research that is required to address this knowledge gap in the convergence between the market and the energy saving potential of WPTs. Further research is needed, for example, on WPT financial aspects such as investments, up-front costs, return on investments, or operating costs. In the concrete case of rigid sails, WPTs are still competitive under conditions of low fuel prices (Atkinson et al., 2018). Likewise, gaps in the knowledge include scenarios for comparative analyses between different cleaner technologies and alternative fuels, along with organizational drives for the adoption of WPTs (Ballini et al., 2017; Tillig and Ringsberg, 2020). Concern about barriers for the uptake of WPTs (Rehmatulla et al., 2017) has led to the suggestion of a need for further research into the heterogeneity of the market in terms of ship types, operational efficiencies in each segment, and chartering characteristics with respect to split incentives. This issue will be discussed in Section 6.

Agent-based modeling (ABM) (Macal and North, 2005; Grimm et al., 2010) has the ability to study how new technologies are adopted in a potential market. In a nutshell, ABM is a bottom-up simulation technique that allows the heterogeneous definition of properties and actions for all the agents contained in a population. One of the most important advantage of using ABM in eco-innovation adoption is the inclusion of agents with very different response patterns, which allows a dynamic bottom-up structure that can converge to a global adoption status. On the other hand, the agents included in ABM (in this problem, shipowners or vessels as potential adopters) do not maintain static positions and reactions, but can evolve throughout the simulation, learning from their own situation and those of the other agents (Chica et al., 2021).

The interaction between agents is also one of the fundamental features of ABM for representing eco-innovation adoption such as in the shipping industry. This interaction makes the role of network analysis pivotal and facilitates the inclusion of networking and demo projects activities as a way to increase the technology awareness and its knowledge. Thus, the use of ABM contribute on how WPT adoption evolves overtime and the results of applying different policies and incentivization strategies, as done in previous works of modeling eco-innovations (Shi et al., 2020; Karslen et al., 2019; Zeng et al., 2020; Rai and Robinson, 2015). With respect to WPT in shipping, previous research employed ABM to model the WPT adoption based on theoretical considerations of costs, fuel savings, and policy characteristics (Karslen et al., 2019). These authors suggested follow-up studies that focus on demonstration projects as a knowledge creation policy for WPTs and explore the connections between modeling (ABM) and the design of demonstration projects to maximize their uptake impact (Karslen et al., 2019).

This paper complements and expands on previous research about the diffusion of WPTs in international shipping by addressing the overall research question "In which scenarios will the heterogeneous global shipping fleet adopt different types of WPT as a retrofit alternative?" The paper develops an agent-based model by integrating Bass diffusion theory and social networks through the model of an heterogeneous sample of vessels and three different types of WPT. To model the diffusion potential of WPTs, scenarios are developed considering currently discussed policies in international shipping (EU and IMO), such as the carbon levy, but also the variation of fuel prices in international markets. The study expands on previous knowledge by integrating into the modeling real world data as part of a European Union (EU) funded project[1] to test five pilots of three different types of WPT in the North Sea region.

In addition, and in contrast with previous studies, the paper benefits from a close feedback from three WPT suppliers involved in the EU project. Thus, and in comparison with existing WPT studies, this work models more than one type of WPT. To exploit the advantages of ABM with respect to heterogeneity, the study also integrates more than one shipping segment by integrating fuel consumption data calculated from the Clarksons World Fleet Register (Clarksons, 2022).

In our study, validation of the diffusion mechanisms of WPT is first carried out by taking into account previous energy studies. Subsequently, we compare the adoption of the three WPT options under different fuel and sailing distance conditions. Finally, we explore incentivization policies based on demonstration projects (and hence related to the awareness of the technology), involving installation cost subsidies and tax on fuel consumption, and combinations thereof. The study

[1] WASP (Wind Assisted Ship Propulsion) project, funded by the Interreg North Sea Europe programme, part of the European Regional Development Fund (ERDF) (https://northsearegion.edu/wasp).

aims to identify any variation on the choice of a specific WPT option when injecting the policies to boost adoption such as those focus on installation costs and fuel taxes. Finally, the insights obtained from the simulations will allow the identification of alternative business models, as a potential way to reduce WPT introduction barriers.

2. Related works

This section provides an analytical framework to understand under which circumstances users adopt cleaner technologies and in concrete undertake green retrofit projects. The analytical framework is thus structured in two interrelated parts. The first part contextualizes WPTs in terms of requirements for green retrofitting projects. The second part integrates the key inputs of green retrofit projects and WPTs in the context of ABM methodological considerations following previous research.

2.1. Wind-assisted propulsion technologies

The use of wind propulsion for ships is an ancient technological development which has re-emerged in line with the need to decarbonize shipping (Atkinson et al., 2018). Wind can be considered a free and renewable source of energy given the lack of friction it faces in open waters compared to land, and thus has a comparative advantage over other emerging "cleaner" propulsion technologies in shipping (Talluri et al., 2016).

A variety of modernized wind propulsion devices are being developed with the primary purpose of reducing fuel consumption and air polluting emissions (Ballini et al., 2017). These technologies can either optimize wind if used in combination with conventional power sources (wind-assisted ship propulsion) or as the primary source of propulsion when the conventional engine is used only exceptionally (De Beukelaer, 2022). After certain technological developments in the 1980s, the main driver of WPT adoption has not been for it to be installed as the main form of propulsion but rather as a retrofit in existing ships to reduce fuel consumption (Atkinson et al., 2018; Yuankui et al., 2014). Hybridization is thus considered key for the further adoption of WPTs in shipping fleets, with wind propulsion assisting the main diesel or bio-diesel engines which serve to ensure the schedule is maintained (Mander, 2017). Different WPTs have been developed and work in slightly different ways, but have the common purpose of providing wind-based propulsion power for the vessel as wind speed increases and of reducing voyage time (Ballini et al., 2017; Yuankui et al., 2014). Commercially available WPTs can be grouped into three categories (Mander, 2017; Rojon and Dieperink, 2014): towing kites, sails and Flettner rotors. Other reported but less diffused technologies in commercial shipping include wind turbines and hull sails (Chou et al., 2021).

The first category, towing kites, allows the ship to benefit from wind lift at high altitudes. The name was used for a number of prototypes created by suppliers such as SkySails in the early 2010s (Chou et al., 2021). More recently, Zhang et al. (2021) compared the economic and technical feasibility of installing towing kites on the ship's bow (parafoils) with the use of Flettner rotors. The study considered the Gibraltar to Panama round route with a Supramax bulk carrier, engine type MAN 6S50ME-B9, with a cruise speed of 14.4 knots, a load of 82.9%, and a daily fuel consumption of 25 tonnes of fuel. The simulation reported a fuel saving of around 1%. The potential of combining weather routing tools with WPTs as a way to increase fuel savings was also highlighted.

The second WPT category comprises both rigid and soft sails, which are variations of traditional sails but with modern features (Chou et al., 2021). Several rigid sails models have been considered in the literature, with examples including the Japan Marine Machinery Development Association (JAMDA) and Walker wingsail-type rigid sails in the 1980s, which yielded a fuel consumption reduction of between 10% and 30% in wind favorable conditions (Atkinson et al., 2018). Suction wings constitute another type of rigid sail, generating upward lifting forces analogous to airplanes. Suppliers include Econowind, with models such as Ventifoil. These models include internal fans and wings with vents (Chou et al., 2021). Soft sails are found in models such as Pinta-Rig, DynaRig, delta-wing sails and FastRigs. DynaRig is gaining in popularity given its maneuverability and safety characteristics (Lu and Ringsberg, 2020). WPTs can also be combined in hybrid sail concepts which incorporate design components of soft and rigid sails. Examples include the Japanese National Maritime Research Institute's hybrid sail concept, or the DynaRig. However, it has been reported that neither of these concepts is commercially viable due to their high costs (Atkinson et al., 2018).

Flettner rotors comprise the third and most commercially diffuse WPT. They have been widely simulated and are well known by policy makers (Chou et al., 2021). This technology originated 100 years ago as a result of tests with the ships Buckau and Barbara (Ammar and Seddiek, 2021). The technology, however, never took off because of the competition with fossil fuel-powered vessels (Mander, 2017). Flettner rotors work under the Magnus effect, which generates lifting and drag forces in the spinning electric motor-aided cylinder aboard the vessel (Ammar and Seddiek, 2021). Given the extensive interest in Flettner rotors, research has been conducted on several parameters that influence its aerodynamic performance. Bordogna et al. (2020), for example, considered the velocity ratio, endplate size and the aspect ratio. In addition, several real-life experiments and desk studies have reported on the inclusion of several Flettner rotors in the installation layout to boost the fuel saving potential (Bordogna et al., 2020; Lindstad et al., 2022b). Lindstad et al. (2022b) provided an example of dry bulkers which require tiltable Flettner rotors to avoid conflict with hatches, cranes or other port-related infrastructure, proposing use of 4 Flettner rotors with a height of 26 m, diameter of 4 m and a distance of 29.6 m between them on board a 200 m Supramax. Tillig and Ringsberg (2020) reviewed previous studies of Flettner rotor simulations and real-world trials, concluding that their use could lead to large potential savings in installation and maintenance costs of up to 40% considering different routes and sailing conditions. Citing other simulations and trails, a similar conclusion about their high flexibility and large fuel reduction potential was shared by Nyanya et al. (2021).

In short, different researchers have reported about WPTs in the early stages of diffusion throughout the industry, with different types and designs competing in the test and pilot phases (Mander, 2017; Rojon and Dieperink, 2014). These test and pilot phases can be also seen as "niches" which seek to create bonds with the legal and economic regime of shipping services by balancing innovative technological development projects (in the line of sails or towing kits), while other players keep traditional sails in use (De Beukelaer, 2022; Mander, 2017).

Notwithstanding this similarity in operational principles, fuel savings using wind propulsion devices on ships depend on the ship design (rig and hull), operation speed and wind speeds and directions (Rehmatulla et al., 2017). The IMO MECP (IMO, 2021) concluded that WPTs can be accommodated as an auxiliary source of power in the calculation of EEDI and EEXI. Chou et al. (2021) reviewed studies of CO_2 emission savings from the installation of WPTs and highlighted the importance of their role in the IMO strategy to reduce GHG emissions of international shipping.

The financial appeal of reducing operational costs is a key driver for shipping companies to embrace wind propulsion, and several studies have calculated the potential economic benefits of WPTs (Ammar and Seddiek, 2021; Ballini et al., 2017; Chou et al., 2021; Karslen et al., 2019; Lu and Ringsberg, 2020; Tillig and Ringsberg, 2020; Zhang et al., 2021). One common conclusion is that fuel prices need to be high for WPT solutions to be competitive (Lindstad et al., 2022b). Other researchers have pointed out the importance of the type of vessel when it comes to the financial benefits to be gained, with particular reference to ocean-going low-speed bulk carriers and oil tankers. The technical reason is the capacity of these vessels to accommodate additional wind propulsion structures on deck (Nyanya et al., 2021).

In addition to a dependence on high fuel prices as a potential factor constraining the diffusion of WPT, other research studies have indicated several other barriers that hinder the uptake of WPTs (Pomaska et al., 2021; Rehmatulla et al., 2017). These include the cost and access of capital, financial and economic constraints, market constraints and split incentives, lack of trusted information, safety and reliability concerns, technical uncertainties, institutional barriers like regulations in place, and poor knowledge infrastructure (Pomaska et al., 2021). Some of these barriers, namely split incentives and the risk perception of the technology, directly concern potential WPT users and constitute a limitation to potential investment (Rehmatulla et al., 2017). Split incentives are connected to the distribution of fuel and maintenance costs between charterer and shipowner in the time charter. The duration of a single time charter contract also has consequences as to whether investing in a WPT will be paid back through fuel savings over the course of the duration of the contract. Risks include concerns about structural integrity, cargo handling, issues of how non-retractable WPTs may interfere with port infrastructure, and ship stability when retrofitted with WPTs (Rehmatulla et al., 2017).

2.2. Diffusion of green technology retrofits through agent-based modeling

Agent-based modeling (ABM) is an increasingly popular research method when the aim is to analyze the adoption of green products and eco-innovations by consumers or promotion policies for cleaner technologies (Ramkumar et al., 2022; Shi et al., 2020). ABM originates from complex systems theories, based on the principles that rules governing the behavior of agents at the micro level (individual agents) can concatenate to simulate what happens at a macro scale (society, market) (Wilensky and Rand, 2015). ABM is thus a computer model based on simulated autonomous agents which are embedded in an environmental setting (McCoy and Lyons, 2014). Common applications of ABM with respect to the adoption of cleaner technologies and eco-innovations include electrical vehicles (McCoy and Lyons, 2014; Shafiei et al., 2012; Zhang et al., 2011), shipping (Karslen et al., 2019), energy supply (Kowalska-Pyzalska et al., 2014) or household heating systems (Sopha et al., 2013). In the electrical vehicle (EV) sector several practical, theoretical and policy-based contributions have emerged from this type of research methodology, including the technological forecasting of innovation diffusion in the EV market (Massiani and Gohs, 2015), consumer behavior in regards to the acceptance of EV in Iceland and long-term effects in connection with tax incentives and energy prices (Shafiei et al., 2012), cluster identification of early adopters for their association with geographical distribution patterns and to better address planning policies (McCoy and Lyons, 2014), and a dynamic marketplace simulation centered on the interactions of technological push, regulatory push and market pull among EV manufacturers (Zhang et al., 2011).

In the sector of energy efficient technologies, studies have been made on the relationship between the quality of information for potential users and technological acceptance among small and medium-sized enterprises, and how inter-firm networks interrelate with the information flow and the quality of the technological diffusion (Shi et al., 2020). In the electricity market of cleaner energy supply, research has centered on consumer attitudes and behaviors and how external factors such as marketing campaigns, public policy or market-based incentives influence consumer decisions in regards to the electricity market (Kowalska-Pyzalska et al., 2014). In the shipping sector, applications of ABM and closely related methodologies have been made in the analysis of policies promoting the diffusion of cleaner shipping technologies. Karslen et al. (2019) analyzed imperfect agent information and split incentives, and their relationship with climate-energy policies in the diffusion of one type of WPT, Flettner rotors. In another study, Xu et al. (2021) relied on evolutionary game theory and ABM to simulate stakeholder interests, the role of regional governance and regulations in the diffusion of electric inland ships in China.

When modeling the adoption of cleaner technologies, a number of characteristics make this tool appropriate. For example, the need to consider the heterogeneity of technology suppliers and adopters is often mentioned as an advantage of the use of ABMs, which allow, for instance, to attribute well-defined characteristics to adopters as well as different examples of the same type of technology such as different brands of electrical cars (Shafiei et al., 2012; Zhang et al., 2011). One advantage of ABM over other methodologies lies in the possibility to observe aggregated micro-level interactions at the macro-level, which is where policy effects are primarily observed (Zhang et al., 2011). In one application addressing household heating technologies, Sopha et al. (2013) designed an ABM which simulates how policy interventions impact the decisions of households to adopt more efficient heating systems, arguing that policy designers should assess beforehand how different configurations of the policy might incentivize consumers in their choices. Similarly, ABM rules allow to program aspects such as network effects on the adoption of cleaner technologies (Ramkumar et al., 2022), as well as marketing concepts such as word-of-mouth, which is a type of social influence in which some users are motivated to adopt a given product following the desire to imitate their peers (Shafiei et al., 2012). An often highlighted benefit of ABM is its ability to apply analogies to lab experiments which at societal scale are impossible to carry out. For example, large scale surveys of million of consumers every day are unrealistic, but it is possible to do an ABM computer simulation through, for instance, policy and market scenario representations. Such flexibility in the use of ABM allows to understand the effects of given combinations of market and political conditions (Karslen et al., 2019; Kowalska-Pyzalska et al., 2014).

A number of studies have addressed the relationship between cleaner technologies and adoption factors. Social network characteristics and the position of a given actor in the network influence the likelihood of the adoption of cleaner technologies, but these are just two of multiple possible drivers that can explain the adoption of cleaner technologies (Ramkumar et al., 2022). Studying cleaner energy sources, Kowalska-Pyzalska et al. (2014), highlighted the role of consumer opinion and its susceptibility to change as a key variable when modeling the adoption of clean technologies through ABM methods. “Adopting a technology” is a process, which follows firstly the formation of an opinion about the particular technology. In this process, the focal actor obtains information from several sources to gain an opinion, including the mass media but also other industrial actors through a word-of-mouth (WOM) process. After the formation of an opinion follows the decision to adopt or not the technology, and subsequently the confirmation of the decision (Kowalska-Pyzalska et al., 2014). Other research, such as that by Pakravan and MacCarty (Pakravan and MacCarty, 2020), has argued that technological adoption is more of a continuous process which requires a better understanding of user intentions and how these intentions translate into behavior, for example in connection to the environment and health aspects as preconditions for the adoption of a technology. In line with other research measuring intentions and behavior (Zhang et al., 2021), the theory of planned behavior (Ajzen, 1991) has been used to disentangle the connections between intentions and behavior.

The analytical framework introduced following previous research studies indicates that green retrofitting projects can be considered a particular kind of cleaner technology adoption. These types of project require a behavioral motivation for users to adopt the technology. WPTs represent a cleaner technological solution for green retrofitting on board older vessels to reduce fuel use and thus help the maritime industry decarbonize operations. However, very little research has been conducted addressing the drivers of shipping companies in the decision to retrofit vessels. ABM methods have been used in a broad range of contexts and technological sectors to model user responses to changing market and policy scenarios in order to promote the adoption of cleaner technologies. In the maritime industry, previous research has addressed both electrical ships and wind-assisted ship diffusion.

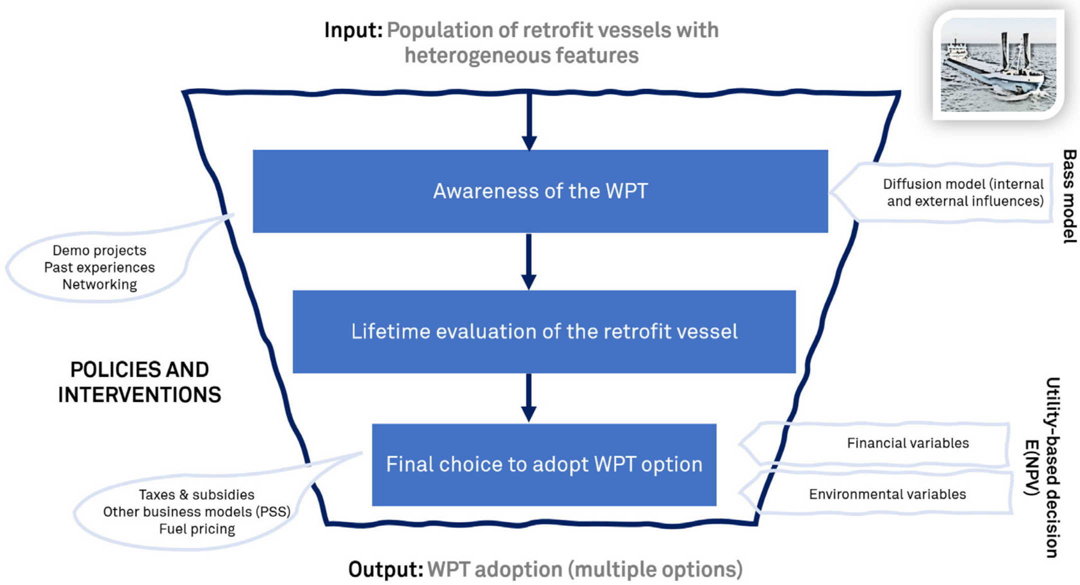

Fig. 1. Diagram with the general phases, policies to be injected and paradigms used in the agent-based proposal for multi-product WPT adoption.

3. Model

This section provides details about the ABM for WPT adoption. First, Section 3.1 presents the general features of the model. The population of vessels and WPT options are described in Section 3.2. The social network of vessels is described in Section 3.3 and the awareness mechanism of the WPT innovation using the Bass model is given in Section 3.4. Finally, the decision-making process for choosing the WPT option is given in Section 3.5.

3.1. General structure

The agent-based model represents a population of vessels Z with their heterogeneous features for each vessel i and a set O of WPT options, also having their heterogeneous features for each $j \in O$. The model mimics WPT adoption over time for T time steps in a terminating simulation model. Each time step t of the simulation represents a month, as done before in similar models because of its sufficient granularity. Since the goal of this modeling is the case of the retrofit maritime industry, the default case technology of a vessel i is to have a fuel-based technology. Therefore, fuel technology is not an adoption option in O because most of the vessels start with a 100% fuel-based approach and, when a WPT option is adopted, it is not common to reverse the technology. Thus, the adoption decision for a vessel in the model ends if any of the WPT options available has already been adopted.

The model has two different stages: an eco-innovation awareness and an utility-based vessel adoption of a WPT option. First, eco-innovation awareness is considered using the agent-based Bass model (Bass, 2004; Chica and Rand, 2017), and second, choosing from among the available options for each specific vessel after having this awareness is based on a decision-making heuristic. The scheme of our proposed model is depicted in Fig. 1, while Fig. 2 shows a flowchart of the mechanisms of the model for WPT adoption.

3.2. Main features of the vessels and WPT options

The population of vessels Z with size N includes heterogeneous vessels that belong to different shipowners. The main features of each vessel i of the population are the following:

- $y_i^0 \in \{1, \dots, Y\}$: The age of the vessel in years. This age is used to calculate the remaining months of use of the retrofit population (r_i) considering a global maximum lifetime of 30 years for a vessel ($Y = 30$).
- κ_i: The expected fuel consumption of the vessel i under averaged climatic conditions and maritime operations.
- $a_i \in \{0, 1\}$: a binary variable for those vessels that have knowledge or awareness about the WPT. This variable is activated ($a_i = 1$) by the Bass diffusion model explained in Section 3.4.
- $o_i \in \{0, 1, \dots, |O|\}$: is the technological option selected by the vessel. If a vessel has a fuel-based option, then $o_i = 0$. $o_i > 0$ when a WPT is adopted.

Apart from the population of vessels, we also define a set of wind-based clean technological options O. Each WPT option $j \in O$ has the following features, fixed for all the vessels in the population:

- C_j: the monthly maintenance cost when having alternative j in a vessel.
- K_j: the installation or capital costs for the j alternative.
- $\sigma_j \in [0, 1]$: the fuel consumption reduction ratio when the WPT option is installed in a vessel.

3.3. Social network of vessels

The vessels of population N are connected by an artificial social network (Barabási and Albert, 1999; Watts and Strogatz, 1998). A social network defines the relationship between different vessels for a word-of-mouth (WOM) process (Watts and Dodds, 2007). In this case, we assume the WOM is realized by vessels and not by their shipowners to increase the granularity of the process. In the proposed model, we select a scale-free (SF) network topology because many real-world networks match this topology (Barabási and Albert, 1999; Newman and Barabási, 2006). A SF network has a power-law degree distribution, meaning that most of the nodes have few connections but a few nodes have a lot (i.e., hubs of the networks).

It is a common approach to approximate a real social network with a synthetically generated preferential attachment network (Barabási

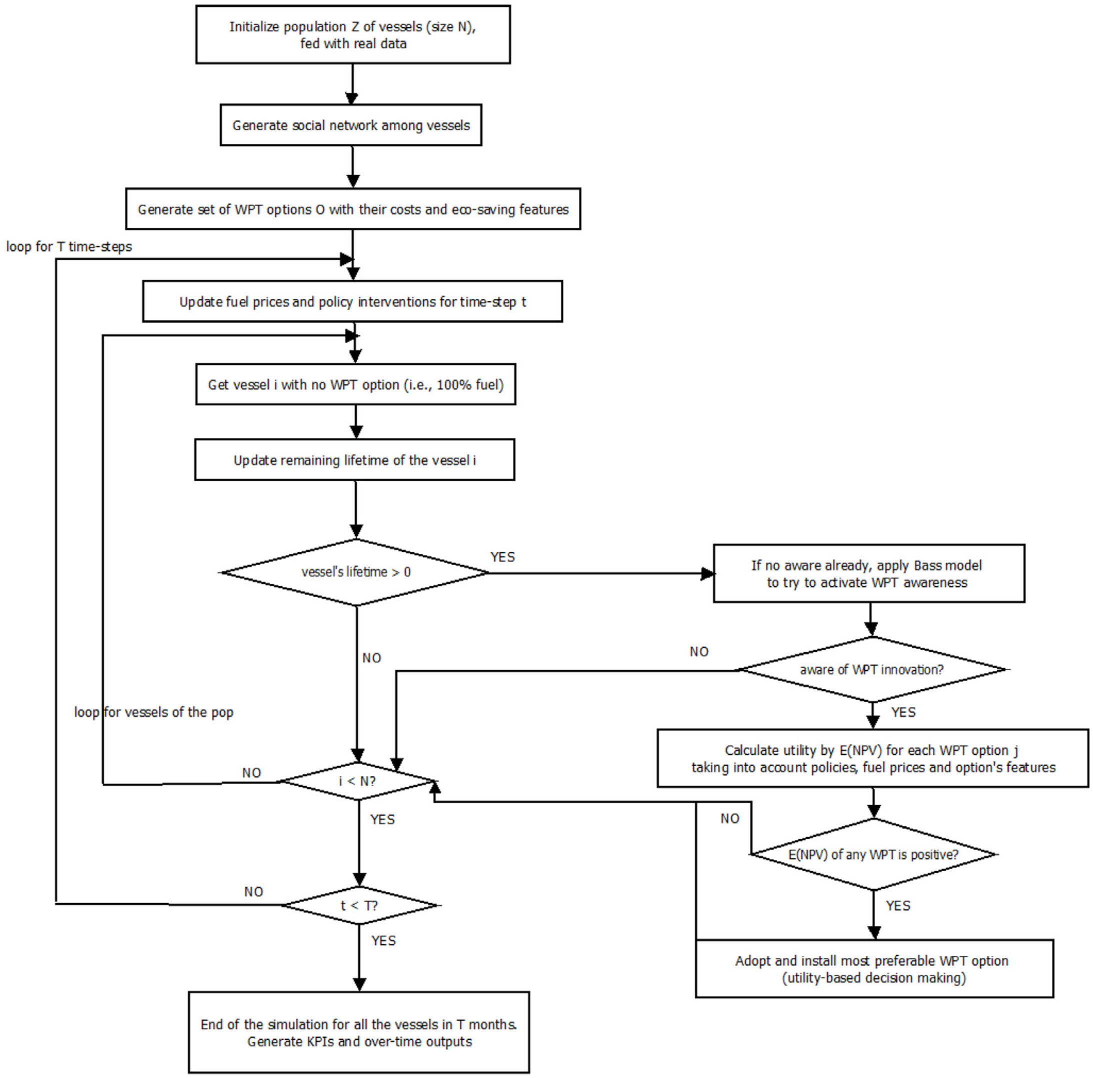

Fig. 2. Flowchart of the agent-based model for adopting multiple WPT options in a population of retrofit vessels.

and Albert, 1999) when there is no data about the features of the network (Overgoor et al., 2019). We generate the SF network of the model using the Barabasi–Albert (BA) preferential attachment algorithm (Barabási and Albert, 1999) which allows to generate SF networks relying on the parameter m. This m parameter modulates the growth rate of the network and its final density. The BA algorithm starts with a fully connected graph with m_0 initial nodes, but at every step the generation algorithm adds a new node to the network and connects it to the m existing nodes which are selected with a probability proportional to the degree of the existing nodes. This procedure continues until the network reaches the desired size. The final average degree of the resulting network can be calculated as $\langle k \rangle = 2m$.

3.4. Awareness of the innovation through the Bass model

The Bass model is an innovation diffusion model of adoption (Bass, 1969; Chica and Rand, 2017) that is widely accepted in the eco-marketing literature (Shi et al., 2020; Zeng et al., 2020; Reddy, 2018). We use here an agent-based version of the Bass model (Bass-ABM) (Rand and Rust, 2011), which assumes independence of the internal (adopter-to-adopter interactions through WOM) and external effects (Chica and Rand, 2017). The Bass-ABM is based on a hazard rate model originally developed to understand the adoption of consumer durables (Bass, 1969). It is a discrete time model in which each agent has one of two states at each time step t (Chica and Rand, 2017): (1) non-adopter or unaware of the eco-innovation or (2) adopter or aware of the eco-innovation. At each time step (i.e., a month in the simulation), a vessel has the opportunity to become aware of the technology. Generally, the Bass model estimates a probability to adopt that changes depending on external advertising and WOM effects. The probability that an agent becomes aware of the WPT due to WOM increases as a function of the fraction of its neighbors who became eco-adopters in previous time steps. Once an agent is aware of the technology, it remains an adopter until the end of the simulation. At each time step, an un-aware vessel agent i can become aware of the WPT due to one of the following two circumstances:

1. External influence — With probability $\hat{p}$, a basic agent becomes an adopter (aware of the technology) due to outside effects (i.e., information from outside the network, where $\hat{p}$ is the external influence coefficient).
2. Internal influence — With probability $\hat{q}$, a basic agent becomes an adopter due to observation of the state of its neighbors, where f is the fraction of neighbors who have adopted and $\hat{q}$ is the internal influence coefficient.

Thus, the probability of an agent being aware of a WPT is given by Eq. (1), where $|K|$ is the number of direct contacts in the network of agent i, and $\hat{a}$ are the number of those direct contacts aware of the technology:

$$p(a_i \rightarrow 1) = \hat{p} + \hat{q}\frac{\hat{a}}{|K|}. \tag{1}$$

3.5. Utility-based decision-making selection of the WPT option

First, a vessel agent i has to be operating within its lifetime, which means its remaining years of operation must be greater than 0 (i.e., $r_i > 0$). This variable r_i is updated every year from the initial age of the vessel (y_i^0). At every time step (i.e., month), an operating vessel agent i, if it is aware of the WPT (i.e., $a_i = 1$), evaluates the existing WPT alternatives O.

The model calculates, for each operating vessel i having a fuel-based technology, the expected net present value ($E(NPV)$) for each WPT option j. Thus, an agent i evaluates the utility $u_{ij}^t = E(NPV)$ for all the WPT options. We follow a simplified version of the $E(NPV)$ definition in Karslen et al. (2019), Lopolito et al. (2013). u_{ij}^t depends on time as it includes the lifetime of the retrofit vessel r_i and its economic costs and savings. Specifically, the utility of an option j for a vessel i is given by Eq. (2).

$$u_{ij}^t = E(NPV)_{ij}^t = \sum_{1}^{r_i} \frac{F_{ij}(t) - C_j}{(1+DR)^t} - K_j \tag{2}$$

where F_{ij} is the monthly fuel savings of vessel i when having option j under averaged conditions by computing the fuel savings factor of the technology (σ_j), the monthly dynamic fuel prices ($f(t)$), and the fuel consumption of the vessel (EC_i). DR is a discount rate, set to 0.085 as in previous models (Karslen et al., 2019; Lopolito et al., 2013). Specifically, fuel savings for vessel i using WPT option j, noted as F_{ij}, is given by $F_{ij}(t) = \sigma_j EC_i f(t)$. This equation integrates the energy consumption estimation EC_i for a given sailing distance of each vessel i, following the procedure described in the Supplementary Information file. Energy consumption (EC), defined in metric tonnes per month, is multiplied by the monetary cost of a fuel tonne f^t and the fuel saving factor of the WPT option σ_j. Therefore, the higher F_{ij} is, the more financially beneficial (i.e., higher utility value) is option j for vessel i.

By taking the defined utility u_{ij}^t, we can inject an extra penalty or tax τ for each *mt* of fuel used by the vessels of the fleet. We can also account for incentives to reduce the installation costs (K_j) by introducing a subsidy monetary value Φ. Therefore, a new utility function is defined in Eq. (3) with a modified version of the previous $E(NPV)$ by incorporating a subsidy Φ and a modified value of monthly fuel saving $F'_{ij}(t) = \sigma_j EC_i(f(t) + \tau)$:

$$\hat{u}_{ij}^t = \sum_{1}^{r_i} \frac{F'_{ij}(t) - C_j}{(1+DR)^t} - K_j + \Phi \tag{3}$$

If all the utility values for the available WPT options (either u_{ij} or $\hat{u}_{ij}$), are negative, the vessel does not consider adopting any of the WPT options and repeats the decision-making process in the next step $t+1$. However, for each WPT option j having a positive utility value, we calculate its probability of acquiring the WPT option $p_i(j)$ through Eq. (4). This equation determines the utility of each alternative for each individual. The probability of choosing alternative j from the available alternatives in the choice set O is calculated using the choice model presented in Eq. (4). Therefore, if there is more than one option with a positive $E(NPV)$, the one with the highest value will have more probability of adoption by vessel i.

$$p_i(j) = \frac{\hat{u}_{ij}}{\sum_{k \in O} \hat{u}_{ik}}. \tag{4}$$

Table 1
Self-reported data about the WPT of the three considered options from three pilots of the EU project WASP.

Pilot name	DWT	Installation costs (K_j)	Monthly maintenance costs (C_j)	Fuel savings (σ_j)
Flettner rotor (vessel pilot #1)	5023	750,000€	1,208.33€	15%
Wingsail twinfoil (vessel pilot #2)	2300	500,000€	833.33€	13.85%
Ventifoil (vessel pilot #3)	3638	321,151€	535.25€	4.94%

4. Real data and experimental setup

This section first explains the costs and fuel savings of the considered WPT options (Section 4.1). Details about real data to generate the features of the population of vessels and technical details about the computational experiments are then given in Section 4.2.

4.1. Data about the WPT options

Thanks to the Wind Assisted Ship Propulsion (WASP) project, funded by the EU, we collected data for three alternatives: Flettner rotors, Ventifoil, and wingsail technologies. Each had been installed in a pilot vessel, allowing us to have capital or installation costs, maintenance costs, and fuel savings. This information is summarized in Table 1. Therefore, parameters C_j, K_j and σ_j are set to those of the table for each of the 3 options ($j = 1, 2, 3$) for the simulations in the experiments.

4.2. Real data about vessels and details of the ABM simulations

In this research we use real vessel data to generate the population Z of vessels for the simulation, extracted from the Clarksons database. We focused on all types of vessel with dead-weight tonnage from 2000 to 6500. After eliminating invalid data, a total of 6009 ships are considered in this research. Thus, we set the size of the population Z to 6009. The initial vessel age is y_i^0 and the estimation of annual energy consumption is κ_i. This estimation procedure is explained in the Supplementary Information document of this work, which can be found online. The mean and standard deviation of the age of the vessels in years is 12 and 5.4, respectively. The dead-weight tonnage has a mean of $4,185.6$ tonnes and standard deviation of $1,255.8$, while the EC in kg/nm has a mean of 23.3 and standard deviation of 24.4.

With respect to the ABM simulations, we have programmed a Java-based simulation software platform to perform the analysis and experiments. This platform was mainly built *ad-hoc* for this WPT adoption model although some functionalities are based on the Mason framework (Luke et al., 2005). For all the experiments shown here we run the model for 30 independent Monte Carlo (MC) realizations with different random seeds. Therefore, all the results shown in this paper are averaged from these 30 independent MC runs. As the time step is monthly, we set $T = 360$ synchronous time steps, meaning 30 years of simulation. We set Y, the maximum lifetime of a vessel, to 30 years as done in previous studies (Karslen et al., 2019).

The fuel price is set to 500 €/mt at the beginning of all the simulations. This value is obtained from both Clarkson's study (Clarksons Research, 2022a) and internal data of the pilot ships of the WASP project. This initial fuel price is increased during the steps of the simulation under two pricing scenarios. First, a monthly-based pessimistic scenario where fuel price is linearly increased by 0.5% for all the 360 months of the simulation. Second, a yearly-based less pessimistic scenario where price is also linearly increased but in a 5% update every year.

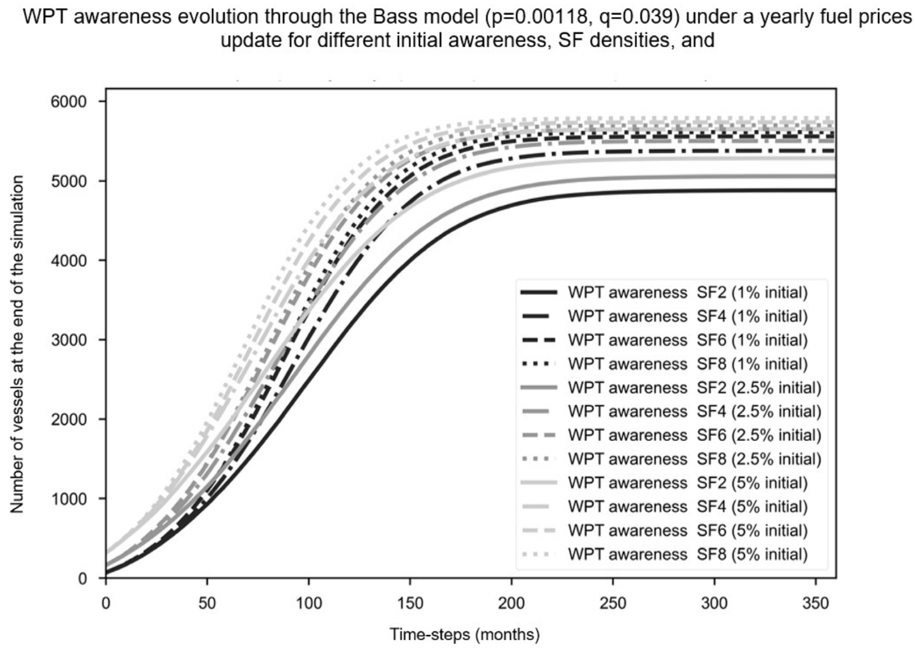

Fig. 3. Evolution of WPT awareness levels for different network densities and different initial awareness of the WPT ($\{1\%, 2.5\%, 5\%\}$) for the 30 years of simulation, with the setting $\{\hat{p} = 0.00118, \hat{q} = 0.039\}$.

Table 2
Main features of the scale-free (SF) network topologies considered in the study.

Network	Average degree	Clustering coefficient	Diameter
SF (BA with $m = 2$)	3.0090	0.0035	12
SF (BA with $m = 4$)	5.0070	0.0044	9
SF (BA with $m = 6$)	7.0100	0.0065	9
SF (BA with $m = 8$)	9.0220	0.0082	8

5. Results

In this section, we analyze the results of a complete set of experiments by means of the described agent-based model, fed with real data. First, we run the model to adjust and analyze the evolution of eco-innovation adoption and the social network conditions (Section 5.1). Later, in Section 5.2, the adoption forecast from the ABM is analyzed. Section 5.3 explores changes in WPT adoption when applying policies of taxes on fuel and installation cost subsidies. Finally, a combination of both policies is applied in Section 5.4.

5.1. Model validation of the diffusion dynamics

In this section, we calibrate the values of the Bass model that simulates the awareness dynamics of the technology. We consider different SF social network densities to be compared in the study (their features are shown in Table 2). For the diffusion process and the Bass model for the awareness of the technology, two parameters $\hat{p}$ and $\hat{q}$ need to be set. As these two coefficients (together with the size of the potential market) determine the shape of the diffusion curve, they are, whenever possible, calibrated based on historical data (da Silva et al., 2020), as these coefficients are sensitive to the adoption process (Massiani and Gohs, 2015). However, although we do not have historical data about WPT in the shipping industry, as we are using the Bass model for awareness of the technology as a condition to apply a decision-making heuristic, the impact of this process is more limited in our model.

In order to calibrate the diffusion process, we studied previous literature on the use of the Bass model for adoption of energy efficient technologies and eco-innovations. More specifically, Heymann et al. (2020) used $\hat{p} = 0.000618$ and $\hat{q} = 0.8736$ for a market size of $1,305,055$ from fitting the model with real data. da Silva et al. (2020) reported $\hat{p} = 0.0015$ and $\hat{q} = 0.002$ for solar water heating in Portugal. Shi et al. (2020) reported $p = 0.018$ and $q = 0.38$, based on a previous study of energy-related problems and calibrated the values for the evolution pattern of the innovation.

In our work, we took previous reported values as seed values for $\hat{p}$ and $\hat{q}$, factorized by month (Massiani and Gohs, 2015, differentiated among monthly and yearly trends), and calibrated them to have an adoption shape like that of Shi et al. (2020), where maximum levels of adoption occur at 12–15 years of simulation. After this calibration process, $\hat{p}$ and $\hat{q}$ were set to $\{0.00118, 0.039\}$. By using these values, we also compared different initial awareness rates of the population and the densities of the SF networks defined in Table 2. The results of the awareness evolution of the technology (without implying the acquisition of any of the WPT options) are shown in Fig. 3.

As can be seen in this table, the diffusion process of awareness has the shape reported in similar energy markets (Shi et al., 2020), and the different conditions of initial awareness and network density do not significantly affect the temporal evolution. We chose a network with $m = 4$ (SF4) for the rest of the study in order to avoid extreme diffusion results with a low initial awareness of 1%, as shipowners are not aware of the technology at the beginning of the simulation.

5.2. WPT adoption in a baseline scenario

In this section, we evaluate WPT adoption when no interventions are injected. The adoption output is observed under the two fuel pricing scenarios defined in Section 4.2, both starting at a price of 500 €/mt. These two scenarios are a pessimistic monthly-based scenario (fuel price is increased by 0.5% for all the 360 months) and a more optimistic yearly-based scenario (fuel price is increased by 5% at each of the 30 years). We set an SF4 network and an initial awareness level of the WPT of 1% with the calibrated $\hat{p}$ and $\hat{q}$ values, as discussed in the previous section.

Fig. 4 compares under these two different fuel pricing scenarios the market share evolution in the next 30 years for the three WPT options. Different sailing distances (26,000, 43,000, 50,000 and $60,000$ nm) were also evaluated because they directly affect the EC of the vessels in

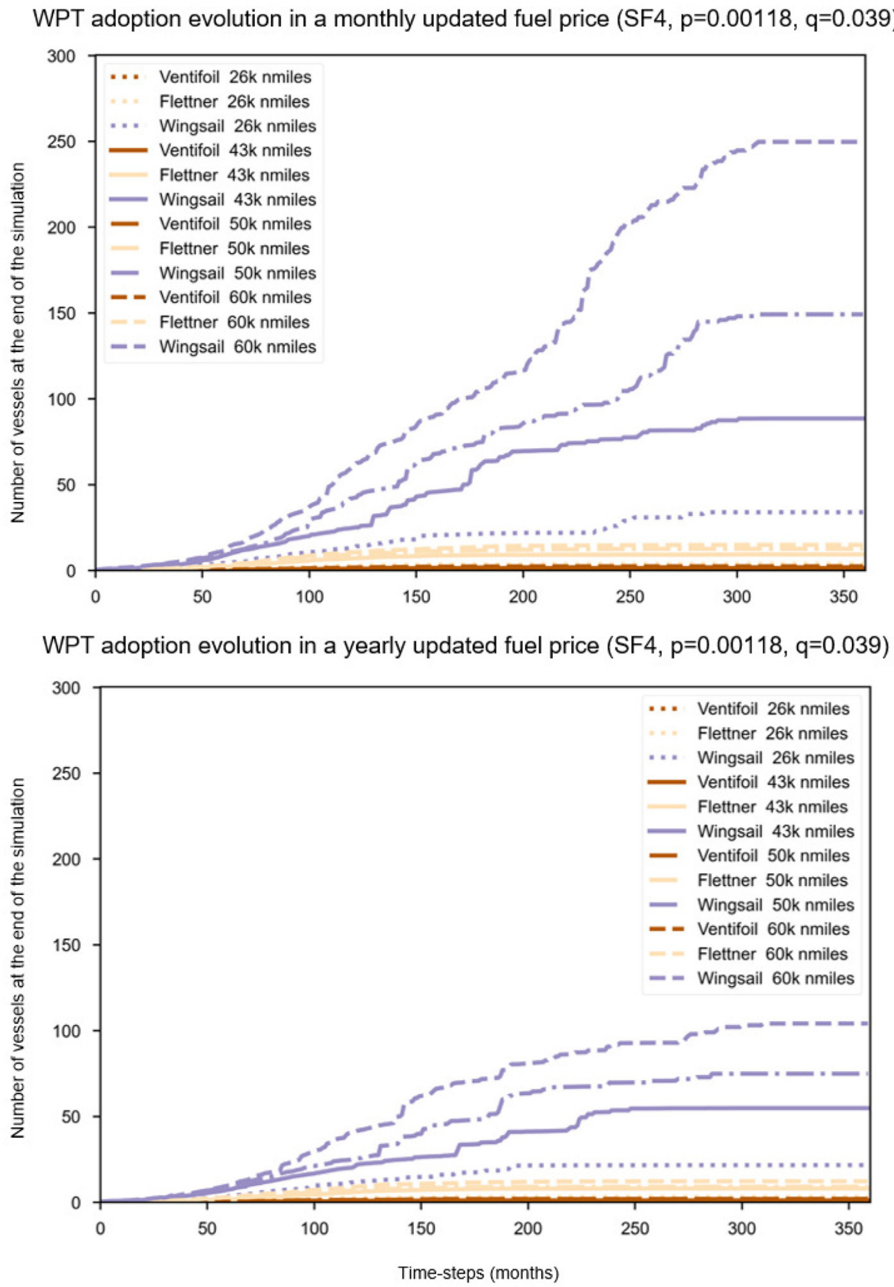

Fig. 4. Adoption evolution of the three WPTs with an initial awareness of 1% for different annual distances of the vessels to estimate EC and under two fuel updating prices: monthly updated fuel prices (upper plot) and yearly updated fuel prices (lower plot). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the population. We remind the reader that each vessel in the population will have a different EC, given the considered scenario of yearly sailing distance.

The results of Fig. 4 show the low level of adoption of the three WPT technologies. The Wingsail option #2 (purple lines) is the most successful technology, although its maximum rate at the end of the 30 years is 250 vessels from a population of 6,009 vessels (4.1%). The highest adoption, as expected, takes place in the first fuel scenario of monthly updated prices as it gives the highest prices; especially when considering an averaged sailing distance of $60,000$ nm, as fuel savings when adopting WPT are higher. The other two WPTs are rarely adopted, mainly because of their high installation cost K_j and low fuel consumption reduction. Nevertheless, acceptance of the three technological options is low without interventions for the whole set of scenarios.

5.3. Incentivization policies of subsidizing installation costs and taxing fuel consumption

It can be seen from the above analysis that the level of WPT adoption in a 30 year horizon is low. In this sub-section, we apply incentivization policies by providing subsidies Φ to the vessels' shipowners to reduce the initial capital or installation costs K_j as well as applying a tax τ on each mt of fuel used by the vessel. Section 3.5 showed how the two variables Φ and τ are applied to the $E(NPV)$ calculation when the vessels make a decision.

The plots of Fig. 5 show a sensitivity analysis of Φ and τ and their implications for the final number of adopters (cell of the heatmaps of the panel). Each of the nine plots of the panel represents the number of vessels that has one of the three WPT options at the end of the simulation period (i.e., 360 months or 30 years) for three sailing distances in

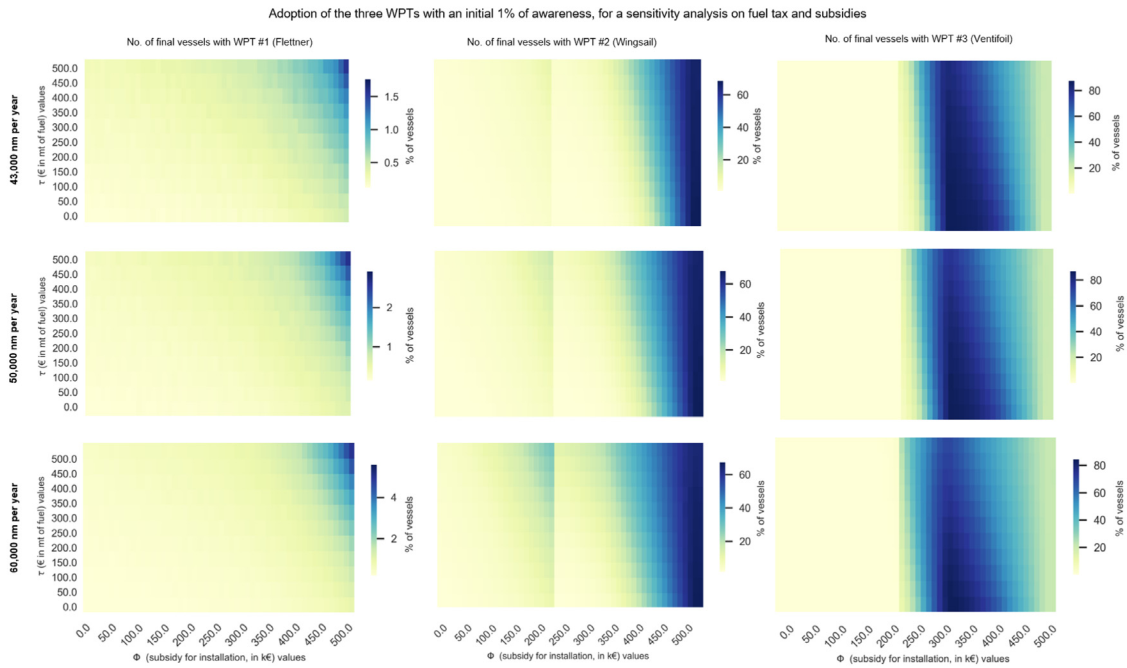

Fig. 5. Heatmaps showing a sensitivity analysis of policies of installation cost subsidies and tax on fuel to incentivize adoption with an initial WPT awareness level of 1% under three scenarios of sailing distance (43,000, 50,000, and 60,000 nm).

a year. The simulations were run with 1% of initial awareness and the calibrated Bass and network topology from the previous sections and the second fuel pricing scenario (i.e., an increment of 5% every year).

It can be seen from this figure that when installation cost subsidies and tax on fuel are low (subsidies less than 100,000 €and tax on fuel less than 300 €) the adoption of the technology is still limited. However, when installation cost subsidies are higher, there is considerably more WPT adoption. The Wingsail option is preferred when the subsidies are at their maximum value. However, when these subsidies (or discounts on installation costs) are in the mid-range, the Ventifoil option #3 is the most competitive as it is the cheapest in terms of installation and maintenance costs. When the tax on fuel and installation cost subsidies are at their maximum values, the Wingsail option seems to be the most chosen because of its higher fuel savings than Ventifoil, although the latter option has lower installation costs. The Flettner rotor option is not massively adopted mainly because of its high cost. Finally, the same dynamics are observed for the three energy consumption (EC) scenarios.

5.4. Combining networking for WPT awareness and policy interventions

In this section, we extend the analysis through the incorporation of an increase in networking activities by raising the initial awareness level of the technology to 10%. The aim is to determine whether an increase in knowledge of the technology affects adoption of the WPT options. We ran the same sensitivity analysis of Φ and τ as in the previous Section 5.3, but with an initial awareness of 10% instead of 1%.

Fig. 6 shows heatmaps of the final percentage of vessels adopting no WPT and of vessels adopting one of the three available technologies at the end of the 30 years of simulation when considering 10% of initial awareness, $43,000$ nm sailing distance, installation cost subsidies, and yearly fuel price updating. As the EC dynamics were previously found to be similar, we focused the sensitivity analysis on a single sailing distance scenario. It can be seen how the final number of vessels with the fuel-only option falls by up to 5% when installation subsidies are above 250,000 €. The Wingsail and Ventifoil options show the highest increase in their market share. However, the Ventifoil option continually gains adopters whereas Wingsail adoption is reduced in favor of Ventifoil, the cheapest option but with lower fuel reduction rates. The reason behind these results is that a higher awareness will generate an anticipated shipowner decision on moving to “cheaper” options. The same applies in the area of 225,000 €to 350,000 €subsidies for installation costs, where Ventifoil gains around 10% of market share with respect to Wingsail. This switching area can also be noticed in Fig. 5 for a lower initial WPT awareness.

Finally, and taking into account the heatmaps of the previous experiments, we propose two values for the installation cost subsidies and tax on fuel to run the model for the 360 steps and see the market share of each WPT option. Fig. 7 shows the evolution of WPT adoption taking into account a 5% initial awareness of the technology (midway value between the 1 and 10% awareness levels of the previous section) and 43k nautical miles for two fuel update price scenarios.

The upper plot of Fig. 7 shows how Ventifoil can be adopted by almost 50% of the vessels at the end of the simulation. This is the option of the majority, the cheapest one although the one saving less fuel. The combination of networking effects and installation subsidies can therefore achieve an important adoption of one of the WPT technologies and mark directions on how to promote WPT adoption.

6. Discussion

With respect to the methods and model, we can highlight the following novelties. Firstly, it is the first adoption model for eco-innovations that includes more than one technology (i.e., three WPTs). Secondly, our model considers two stages in the adoption phase, one related to awareness of the technology and networking/demo effects, and the second mainly to maritime industry economic concerns. These characteristics differentiate the resulting model from previous applications of ABM in the adoption of eco-innovations. The main focus in the published literature in this field has been on electric vehicle (EV) uptake, but few studies have considered other transportation sectors. For instance, Shafiei et al. (2012) simulated the diffusion of EVs in the period 2012–2030 by combining policy and market scenarios along with customer acceptance, with policy mixes that support the diffusion of EV (dropping tax on EVs, reduction in import taxes, charging infrastructure support). Other simulation efforts have aimed to understand

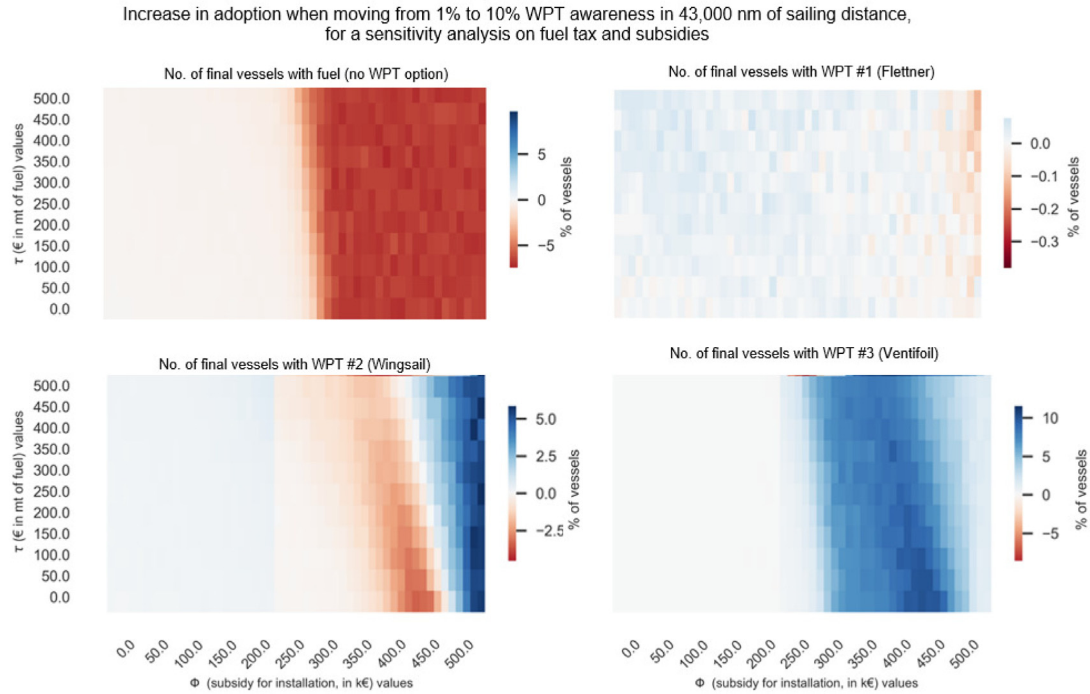

Fig. 6. Heatmaps showing the difference when setting an initial WPT awareness level of 10% compared to 1% on a sensitivity analysis of installation cost subsidies and tax applied to mt of fuel as incentivization policies. The simulation was carried out considering a sailing distance of 43,000 nautical miles per year and yearly updated fuel prices.

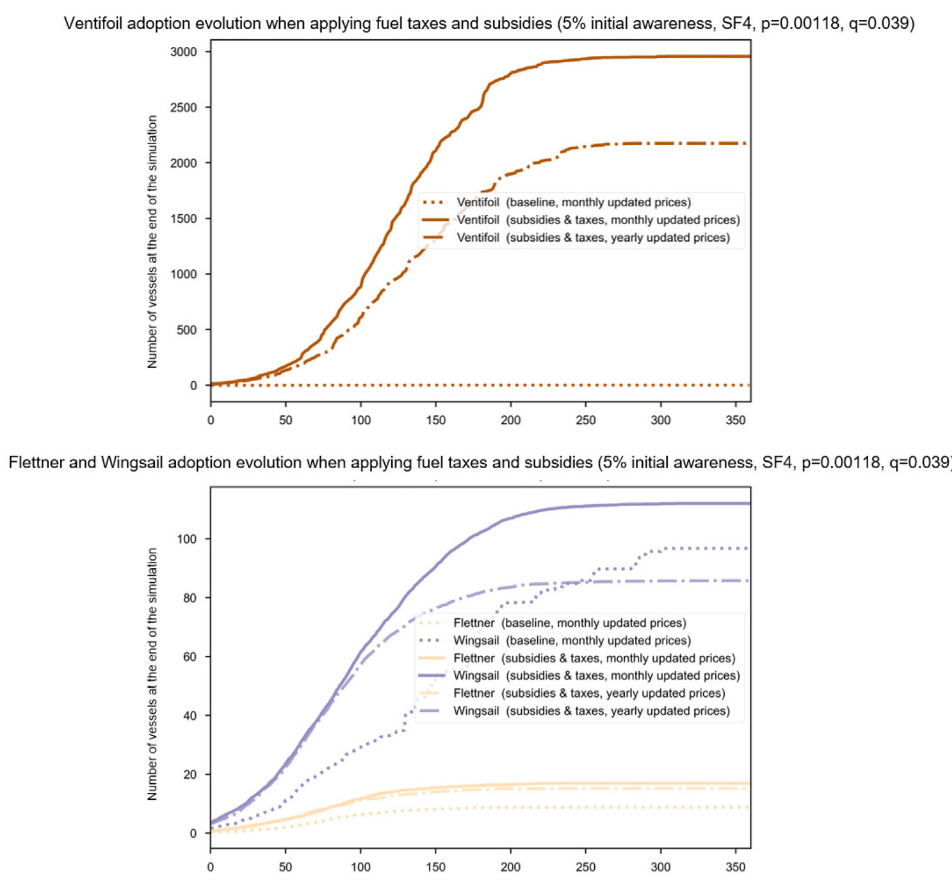

Fig. 7. WPT adoption after applying a tax on fuel $\tau = 100$ and a subsidy of 275,000 for installation costs. Upper plot shows the evolution of the Ventifoil option and the lower plot the evolution of the Flettner and Wingsail options. We compare a baseline (no application of tax on fuel or installation cost subsidies) with application of the policy when having both monthly and yearly updated fuel prices. Initial awareness is set to 5%, and nautical miles to $43,000$ nm to compute the energy consumption.

the consumer adoption of particular practices such as dynamic tariffs or improved ecological stoves, but with a strong focus on measuring the divide between intentions and behavior (Kowalska-Pyzalska et al., 2014; Pakravan and MacCarty, 2020).

Our model also differs from a previous contribution modeling the diffusion of energy efficient technologies (EETs) (Shi et al., 2020), which exclusively focused on the diffusion of information about EETs within a network of enterprises and the formation of opinions about those EETs. Thirdly, our study directly addresses the need for simulations with real data, heterogeneous fleet characteristics and pilot trials. The model is fed with real vessel data and incorporates the remaining years of operation in order to obtain a realistic expected net present value $E(NPV)$. Interestingly, previous research has also emphasized the need to stimulate knowledge about WPTs as a way to increase the legitimacy of the technology among industry players both from a policy point of view (Rojon and Dieperink, 2014) as well as through pilot projects (full trials) in combination with market-based measures (MBMs) (Karslen et al., 2019; Rehmatulla et al., 2017). Previous research modeled Flettner rotor adoption and acknowledged the effects of high fuel prices and split incentives arising from chartering structures and low awareness about the technology as the main drivers keeping adoption levels low (Karslen et al., 2019).

Fourthly, the model is not overloaded with assumptions about parameters, but restricted to well-known processes such as the Bass model and utility maximization, and is enriched with real data for most of the parameters while calibrating the dynamics with observed patterns in the closest models in the literature. These two aspects of the model expand on a previous application of ABM in the analysis of Flettner rotors as a single WPT (Karslen et al., 2019). The referenced study focused on the reduction of CO2 emissions with simulations of carbon market prices as a policy instrument and highlighted the role of pilot projects, but with the drawback of using theoretical considerations in each stage.

From a managerial perspective, the main insights that can be inferred from the results are the following. First, without interventions, adoption of any of the three WPT options is very limited, with Wingsail (option #2) the preferred one but with a final adoption of just 4% at the end of the 30 years of simulation. If policies related to subsidies for installation costs and taxes on fuel are introduced, the Wingsail and Ventifoil technologies (options #2 and #3, respectively) are adopted in considerable numbers when enough effort is made to reduce the installation costs, which seems to be the hardest adoption barrier to overcome. Through the analysis that has been made, we see how there is a shift in the adopted technology between WPT options #2 and #3 depending on the installation cost subsidies. When subsidies are in the mid-range, vessels adopt Ventifoil (WPT option #3). However, when subsidies are at their maximum values, Wingsail is the preferred option because of its higher fuel savings. Installation cost subsidies seem to have a greater influence on the dynamics than tax on fuel. This is related to the previously mentioned barrier of installation costs for WPT adoption. When combining networking effects to promote a higher awareness of the technology together with subsidies, we see how the adoption of the three WPT options increases by up to 5%. More interestingly, we see that increasing awareness through networking boosts and favors Ventifoil, the cheapest technology, causing Wingsail to lose adopters. To summarize, an important insight of this study is the importance of the installation cost barrier, and how installation cost subsidies are more critical than tax on fuel. Therefore, policies to promote adoption should focus on subsidizing installation and maintenance costs. A combination of networking effects and installation subsidies can result in almost 50% of the vessels adopting one of the technologies.

This concrete business- and innovation-oriented support policy differs significantly from the results of previous research addressing policy recommendations for the promotion of WPT technologies. Some studies have centered on MBMs, such as reduced port fees and reduced insurance premiums (Ballini et al., 2017). Others have considered the financing of research and development initiatives (Rojon and Dieperink, 2014), and fuel prices in terms of either fuel levies or requirements to use alternative fuels which would serve as a driver to switch to, for example, slow steaming or wind-assisted ship propulsion to reduce fuel expenditure (Tillig and Ringsberg, 2020). Consideration has also been given to the implementation of a "carbon" tax on emitted mt of CO_2 gases as a way to address potential barriers and make WPTs more attractive to shipowners (Karslen et al., 2019; Metzger, 2022).

Our findings thus provide a more nuanced perception of how different levels of industry subsidies can attract the interest of shipowners and serve as a strategy to address barriers such as cost and access of capital at the market level (Pomaska et al., 2021). Our findings suggest that such a strategy has limitations when the goal is an heterogeneous segment of ships and WPTs. As pointed out by Pomaska et al. (2021), product-as-service can also be a possible strategy at the level of market structure to address market barriers. Here, the suppliers earn profit throughout the life cycle of the product through a subscription fee which is included in the operational costs of the shipping company (Rivas-Hermann et al., 2015). Otherwise, high government-sourced incentives such as subsidies of up to 50% of the initial installation costs are required for significant levels of WPT adoption. Since this research focuses on the retrofitting of existing ships and not new ship constructions, incentives of this type should be in line with the current ambitious goals of reducing CO_2 emissions from ships, as well as the latest policy developments. As pointed out in Clarksons Research (2022b), energy saving technologies (ESTs) are already installed in 23.6% of the global fleet and the demand for ESTs will continue to increase as a result of new policy changes at EU level as, for example, the inclusion of ships over 5000 GT in the EU's ETS directive from the start of 2023.

Although subsidies and public programs are the primary funding sources of current WPT retrofit cases, whether the shipowner can finance the acquisition and installation of the WPT equipment is still one of the significant barriers to the uptake of WPTs. Besides the barrier of access to capital, technical availability is also a significant concern of a shipowner or long-term charter. Due to deck space requirements, not all ships can find a proper technique and WPT devices in the market. Third, as discussed earlier, the retrofit of WPTs sometimes negatively impacts cost efficiency. Many research projects consider internalizing the social cost of CO_2 emissions, e.g., CO_2 tax. However, there is no such regulation in place. Current ship owners cannot receive benefits from this point of view. In addition, the cost efficiency of WPT depends on many issues, e.g., wind conditions, volatility of fuel prices, safety, and reliability (Nelissen et al., 2016). All these factors make the cost efficiency of WPT uncertain and constitute barriers to the dispersion of WPT.

7. Conclusions and future works

In this study, a novel agent-based model is proposed with two different stages (technology awareness and utility-based decision) for a set of possible WPT innovations for the retrofit maritime industry. By using the simulation results of the model, enriched with real data about the vessels and WPT options, different policy interventions were applied to find the optimal way to incentivize WPT adoption. From a computational point of view, the following novel contributions of this study can be highlighted:

- It is the first adoption model in eco-innovations that includes more than one technology. Specifically, three WPT technologies were included in the decision process, using real fuel savings and costs from an EU project.

- The model considers two stages when adopting. The first is related to awareness of the technology and networking/demo effects, while the second stage employs the utility of the net perceived value for each option.
- We do not overload the model's specification with parameter-related assumptions but instead restrict the design of the model to well-known processes such as the Bass model and utility maximization.
- The model is fed with real data from the vessels and includes the remaining years of operation to obtain a realistic net expected profit and the costs to adopt the technology. When no real data is available, we calibrate the dynamics with observed patterns in the closest models found in the literature.

From a managerial point of view, the main insights we observed from the computational study are that, without interventions, the adoption of any of the three WPT options is very limited (i.e., under 5%). The best policies to promote adoption involve the use of subsidies to reduce the installation costs of the WPT for the retrofit vessels, with this being more effective to boost WPT adoption than taxes on fuel. Hybrid policies to promote adoption should focus on networking effects and installation subsidies. Interestingly, another managerial insight is how increasing the awareness of the technology through networking boosts and favors Ventifoil, the cheapest technology, at the expense of the Wingsail technology.

As for future works, we can highlight different paths. Methodologically, an extension of the model could be considered to incorporate other non-WPT options in the set of available options for the vessels (e.g., hydrogen-based technologies). Also, a more theoretical model employing evolutionary game theory (Nowak et al., 2010; Chica et al., 2021) to include decisions from stakeholders can be studied for the maritime industry, as has been done in other fields (Encarnação et al., 2018). Finally, researchers could study new ways of applying the product-service business model, as well as its optimal specification, to generate a higher WPT adoption rate in the retrofit maritime industry.

CRediT authorship contribution statement

Manuel Chica: Conceptualization, Software, Data curation, Methodology, Formal analysis, Writing – original draft, Visualization. **Roberto Rivas Hermann:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Ning Lin:** Data curation, Formal analysis, Writing – original draft, Methodology.

Declaration of competing interest

OR The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.techfore.2023.122559.

References

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.
Ammar, N., Seddiek, I., 2021. Wind assisted propulsion system onboard ships: case study Flettner rotors. Ships Offshore Struct.
Atkinson, G., Nguyen, H., Binns, J., 2018. Considerations regarding the use of rigid sails on modern powered ships. Cogent Eng. 5, 1–20.
Bach, H., Bergek, A., Bjørgum, T., Kenzhegaliyeva, A., Steen, M., 2020. Implementing maritime battery-electric and hydrogen solutions: A technological innovation systems analysis. Transp. Res. D 87, 102492.
Bach, H., Mäkitie, T., Hansen, T., Steen, M., 2021. Blending new and old in sustainability transitions: Technological alignment between fossil fuels and biofuels in Norwegian coastal shipping. Energy Res. Soc. Sci. 74, 101957.
Ballini, F., Ölçer, J., Neumann, D., 2017. Health costs and economic impact of wind assisted ship propulsion. Ocean Eng. 146, 477–485.
Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509–512.
Bass, F.M., 1969. A new product growth model for consumer durables. Manage. Sci. 36, 1057–1079.
Bass, F.M., 2004. Comments on a new product growth for model consumer durables the bass model. Manage. Sci. 50, 1833–1840.
Bordogna, G., Muggiasca, S., Giappino, S., Belloli, M., Keuning, J., Huijsmans, R., 2020. The effects of the aerodynamic interaction on the performance of two flettner rotors. J. Wind Eng. Ind. Aerodyn. 196.
Chica, M., Hernández, J.M., Manrique-de Lara-Peñate, C., Chiong, R., 2021. An evolutionary game model for understanding fraud in consumption taxes [research frontier]. IEEE Comput. Intell. Mag. 16, 62–76.
Chica, M., Rand, W., 2017. Building agent-based decision support systems for word-of-mouth programs. a freemium application. J. Mar. Res. 54, 752–767.
Chou, T., Kosmas, V., Acciaro, M., Renken, K., 2021. A comeback of wind power in shipping: An economic and operational review on the wind-assisted ship propulsion technology. Sustainability 13 (1880).
Clarksons, 2022. World fleet register.
Clarksons Research, 2022a. Fuelling Transition: Tracking the Economic Impact of Emission Reductions & Fuel Changes. Technical Report, Clarksons, London.
Clarksons Research, 2022b. World fleet monitor june 2022. World Fleet Monit. 13.
da Silva, H.B., Uturbey, W., Lopes, B.M., 2020. Market diffusion of household pv systems: Insights using the bass model and solar water heaters market data. Energy Sustain. Dev. 55, 210–220.
De Beukelaer, C., 2022. Tack to the future: is wind propulsion an ecomodernist or degrowth way to decarbonise maritime cargo transport? Clim. Policy 22, 310–319.
Encarnação, S., Santos, F.P., Santos, F.C., Blass, V., Pacheco, J.M., Portugali, J., 2018. Paths to the adoption of electric vehicles: An evolutionary game theoretical approach. Transp. Res. B 113, 24–33.
Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F., 2010. The ODD protocol: a review and first update. Ecol. Model. 221, 2760–2768.
Heymann, F., vom Scheidt, F., Soares, F.J., Duenas, P., Miranda, V., 2020. Forecasting energy technology diffusion in space and time: model design, parameter choice and calibration. IEEE Trans. Sustain. Energy 12, 802–809.
IMO, 2021. Marine Environment Protection Committee (MEPC) 77. pp. 22–26.
IMO, 2022. UN body adopts climate change strategy for shipping.
Karslen, R., Papachristos, G., Rehmatulla, N., 2019. An agent-based model of climate-energy policies to promote wind propulsion technology in shipping. Environ. Innov. Soc. Transit. 31, 33–53.
Kowalska-Pyzalska, A., Maciejowska, K., Suszczyński, K., Sznajd-Weron, K., Weron, R., 2014. Turning green: Agent-based modeling of the adoption of dynamic electricity tariffs. Energy Policy 72, 164–174.
Lindstad, E., Polić, D., Rialland, A., Sandaas, I., Stokke, T., 2022a. Decarbonizing bulk shipping combining ship design and alternative power. Ocean Eng. 266, 112798.
Lindstad, E., Stokke, T., Alteskjær, A., Borgen, H., Sandaas, I., 2022b. Ship of the future —A slender dry-bulker with wind assisted propulsion. Marit. Transp. Res. 3.
Lopolito, A., Morone, P., Taylor, R., 2013. Emerging innovation niches: An agent based model. Res. Policy 42, 1225–1238.
Lu, R., Ringsberg, J., 2020. Ship energy performance study of three wind-assisted ship propulsion technologies including a parametric study of the flettner rotor technology. Ships Offshore Struct. 15, 249–258.
Luke, S., Cioffi-Revilla, C., Panait, L., Sullivan, K., Balan, G., 2005. Mason: A multiagent simulation environment. Simulation 81, 517–527.
Macal, C.M., North, M.J., 2005. Tutorial on agent-based modeling and simulation. In: Proceedings of the Winter Simulation Conference. IEEE, p. 14.
Mander, S., 2017. Slow steaming and a new dawn for wind propulsion: A multi-level analysis of two low carbon shipping transitions. Mar. Policy 75, 210–216.
Massiani, J., Gohs, A., 2015. The choice of bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. Res. Transp. Econ. 50, 17–28.
McCoy, D., Lyons, S., 2014. Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. Energy Res. Soc. Sci. 3, 89–101.
Metzger, D., 2022. Market-based measures and their impact on green shipping technologies. WMU J. Marit. Aff. 21, 3–23.
Nelissen, D., Traut, M., Köler, J., Mao, W., Faber, J., Ahdour, S., 2016. Study on the Analysis of Market Potentials and Market Barriers for Wind Propulsion Technologies for Ships. Technical Report, CE Delft, Delft.
Newman, M., Barabási, D.J., 2006. The Structure and Dynamics of Networks. Princeton University Press.
Nowak, M.A., Tarnita, C.E., Antal, T., 2010. Evolutionary dynamics in structured populations. Philos. Trans. R. Soc. B 365, 19–30.

Nyanya, M., Vu, H., Schöborn, A., Ölçer, A., 2021. Wind and solar assisted ship propulsion optimisation and its application to a bulk carrier. Sustain. Energy Technol. Assess. 47.

Overgoor, G., Chica, M., Rand, W., Weishampel, A., 2019. Letting the computers take over: Using AI to solve marketing problems. Calif. Manage. Rev. 61, 156–185.

Pakravan, M.H., MacCarty, N.A., 2020. Design for clean technology adoption: Integration of usage context, user behavior, and technology performance in design. Trans. ASME, J. Mech. Des. 142, 1–10.

Pomaska, L., Rafaelova, Z., Kosmas, V., Acciaro, M., 2021. Barriers and Overcoming Strategies for Accelerating the Uptake of WASP. Technical Report, Kühne Logistics University, Hamburg.

Prussi, M., Scarlat, N., Acciaro, M., Kosmas, V., 2021. Potential and limiting factors in the use of alternative fuels in the European maritime sector. J. Clean. Prod. 291, 125849.

Rai, V., Robinson, S.A., 2015. Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. Environ. Model. Softw. 70, 163–177.

Ramkumar, S., Mueller, M., Pyka, A., Squazzoni, F., 2022. Diffusion of eco-innovation through inter-firm network targeting: An agent-based model. J. Clean. Prod. 335, 130298.

Rand, W., Rust, R.T., 2011. Agent-based modeling in marketing: Guidelines for rigor. Int. J. Res. Mark. 28, 181–193.

Reddy, B.S., 2018. Economic dynamics and technology diffusion in indian power sector. Energy Policy 120, 425–435.

Rehmatulla, N., Parker, S., Smith, T., Stulgis, V., 2017. Wind technologies: Opportunities and barriers to a low carbon shipping industry. Mar. Policy 75, 217–226.

Rivas-Hermann, R., Köler, J., Scheepens, A., 2015. Innovation in product and services in the shipping retrofit industry: a case study of ballast water treatment systems. J. Clean. Prod. 106, 443–454.

Rojon, I., Dieperink, C., 2014. Blowin' in the wind? Drivers and barriers for the uptake of wind propulsion in international shipping. Energy Policy 67, 394–402.

Shafiei, E., Thorkelsson, H., Ágeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. Technol. Forecast. Soc. Change 79, 1638–1653.

Shi, Y., Zeng, Y., Engo, J., Han, B., Li, Y., Muehleisen, R.T., 2020. Leveraging inter-firm influence in the diffusion of energy efficiency technologies: An agent-based model. Appl. Energy 263, 114641.

Sopha, B.M., Klökner, C.A., Hertwich, E.G., 2013. Adoption and diffusion of heating systems in Norway: Coupling agent-based modeling with empirical research. Environ. Innov. Soc. Transit. 8, 42–61.

Talluri, L., Nalianda, D.K., Kyprianidis, K.G., Nikolaidis, T., Pilidis, P., 2016. Techno economic and environmental assessment of wind assisted marine propulsion systems. Ocean Eng. 121, 301–311.

Thies, F., Ringsberg, J.W., 2022. Wind-assisted, electric, and pure wind propulsion — the path towards zero-emission RoRo ships. Ships Offshore Struct. 1–8.

Tillig, F., Ringsberg, J., 2020. Design, operation and analysis of wind-assisted cargo ships. Ocean Eng. 211.

Watts, D.J., Dodds, P.S., 2007. Influentials, networks, and public opinion formation. J. Consum. Res. 34, 441–458.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of 'small-world' networks. Nature 393, 440–442.

Wilensky, U., Rand, W., 2015. Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo. MIT Press.

Xing, H., Stuart, C., Spence, S., Chen, H., 2021. Alternative fuel options for low carbon maritime transportation: Pathways to 2050. J. Clean. Prod. 297, 126651.

Xu, L., Di, Z., Chen, J., 2021. Evolutionary game of inland shipping pollution control under government co-supervision. Mar. Pollut. Bull. 171, 112730.

Yuankui, L., Yingjun, Z., Feixiang, Z., 2014. Minimal time route for wind-assisted ships. Mar. Technol. Soc. J. 48, 115–124.

Zeng, Y., Dong, P., Shi, Y., Wang, L., Li, Y., 2020. Analyzing the co-evolution of green technology diffusion and consumers' pro-environmental attitudes: An agent-based model. J. Clean. Prod. 256, 120384.

Zhang, T., Gensler, S., Garcia, R., 2011. A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach*. J. Prod. Innov. Manage. 28, 152–168.

Zhang, P., Lozano, J., Wang, Y., 2021. Using flettner rotors and parafoil as alternative propulsion systems for bulk carriers. J. Clean. Prod. 317, 128418.

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