# Kurzfassung

Die Schifffahrtsindustrie wickelt mehr als 90% des weltweiten Handelsvolumens ab und ist für etwa 3% der weltweiten $CO_2$-Emissionen verantwortlich. Gleichzeitig wird erwartet, dass der Handel der Schifffahrtsindustrie bis 2050 im Vergleich zu 2008 um bis zu 130% zunehmen wird. Gleichzeitig wird angestrebt, die Treibhausgasemissionen der Schifffahrtsindustrie bis 2050 auf die Hälfte des Niveaus von 2008 zu reduzieren. Um dieses Ziel zu erreichen, befasst sich diese Arbeit mit einem umfassenden Ansatz zur Optimierung des Schiffsbetriebs, d. h. einem Optimierungsansatz, der gleichzeitig die Routenauswahl, das Energiemanagement, die Propellersteigung und die Motorsteuerung umfasst. Darüber hinaus wird in dieser Arbeit auch die Anwendung von Windantriebssystemen analysiert. Die Optimierung des Schiffsbetriebs wird in Form von Methoden des Reinforcement Learning (RL) durchgeführt. Die Verwendung von RL-basierten Methoden zur gleichzeitigen Optimierung verschiedener Aspekte der Schiffstrajektorie und -steuerung ist ein neuartiger Ansatz im Vergleich zum derzeitigen Stand der Technik und beschreibt die Innovation dieser Arbeit. Insbesondere benötigt der Ansatz kein Modell und steht damit im Gegensatz zu den üblicherweise verwendeten Methoden der Dynamic Programming (DP). Im Vergleich zu traditionellen modellbasierten Methoden sind RL-basierte Methoden deutlich besser geeignet, um mit hoher Systemkomplexität umzugehen. So erlauben RL-basierte Methoden beispielsweise die gleichzeitige (parallele) Betrachtung einer großen Anzahl von Optimierungszielen, während traditionelle Methoden dies entweder nicht können oder in Bezug auf die verfügbare Rechenleistung und den Speicher begrenzt sind. Eine hohe Systemkomplexität ist typisch für eine maritime Anwendung und zeigt den Bedarf an einem geeigneten Optimierungsansatz. Bei Verwendung eines solchen Ansatzes, d. h. eines rein RL-basierten Ansatzes, der gleichzeitig viele verschiedene betriebliche Aspekte berücksichtigt und optimiert, zeigen die Ergebnisse im besten Fall Kraftstoffeinsparungen von bis zu 63,6%. Die Ergebnisse zeigen insbesondere die Wichtigkeit der Parallelisierung der Routenoptimierung mit der Optimierung anderer Steuerungsaspekte. Zur Veranschaulichung dieser Aspekte wird in dieser wissenschaftlichen Arbeit ein Szenario untersucht, das die parallele Optimierung des Energiemanagementsystems (EMS) zusammen mit der Routenwahl umfasst. In diesem Fall führt allein die parallele Optimierung zu einer Kraftstoffreduzierung von bis zu 10%. Schließlich wird gezeigt, dass die Lösung gegenüber einem rein RL-basierten Ansatz weiter verbessert werden kann, wenn die optimierten Routen-, Geschwindigkeits- und Leistungsprofile in einem Nachbearbeitung Schritt zur Durchführung individueller DP-basierter Energiemanagement-Optimierungen verwendet werden. Diese Verbesserung führt zu zusätzlichen Kraftstoffeinsparungen von bis zu 0,76%.

# Abstract

The shipping industry handles over 90% of the global trade volume and is responsible for approximately 3% of global $CO_2$ emissions. Meanwhile, trade by the shipping industry is expected to increase by up to 130% by 2050 compared to 2008. At the same time, the goal is to reduce Green House Gas (GHG) emissions from the shipping industry to half of the 2008 level by 2050. In support of this goal, this thesis is concerned with a comprehensive approach for optimizing the ship's operation, i.e., an optimization approach that simultaneously involves route selection, energy management, propeller pitch, and engine control. In addition, this thesis also analyses the application of wind propulsion systems. The optimization of the ship's operation is implemented in the form of Reinforcement Learning (RL) methods. The use of RL-based methods to simultaneously optimize various aspects of the ship's trajectory and controls is a novel approach compared to the current state-of-art and embodies this thesis' inherent innovation. In particular, the approach does not require a model and is thus in stark contrast to the usually used Dynamic Programming (DP) methods. Compared to traditional model-based methods, RL-based methods are much better suited to deal with high levels of system complexity. As a consequence, RL-based methods facilitate the simultaneous (parallel) consideration of a multitude of optimization goals, while conventional methods either do not or are limited in terms of the available computational power and memory. A high level of system complexity is typical for a maritime application and highlights the need for an adequate optimization approach. Using such an approach, i.e., a purely RL-based approach that simultaneously considers and optimizes many different operational aspects, the results show a best-case fuel saving of up to 63.6%. The results specifically highlight the importance of parallelizing route optimization with the optimization of other control aspects. To exemplify this, a simplified problem involving only the parallel optimization of the Energy Management System (EMS) along with route selection is studied as part of this thesis. For this case alone, the parallel optimization yields a 10% increase in fuel-saving. Ultimately, it is found that the solution emanating from a purely RL-based approach can be further enhanced when the optimized route, speed, and power profiles are used to perform individual DP-based optimizations on the energy management in a post-processing step. This enhancement yields up to 0.76% of additional fuel savings.

# 1 Motivation and Objectives

## 1.1 Motivation

The shipping industry handles more than 90% of global trade and contributes to roughly 3% of global $CO_2$ emissions [28]. Projections indicate that the trade volume is expected to increase by up to 130% by 2050 compared to 2008 figures. Meanwhile, according to the guidelines set by the Marine Environment Protection Committee (MEPC), the goal is to reduce greenhouse gas emissions due to maritime trade to half of 2008 levels by 2050 [47]. This legislation and the need to meet the specified emission targets require significant improvements and optimizations of both ship design and operation. An important aspect of operational optimization is route selection. Unlike passenger cars, ships have more flexibility regarding the selection of available routes. In addition, fuel consumption is strongly influenced by the weather along the route. With reliable weather data, it is possible to predict the ships' fuel consumption. If the route is adequately optimized, rough sea conditions can be avoided, resulting in fuel savings throughout the voyage. Another potential area for optimizing ship operations is the control of the energy management system in ships with hybrid powertrains. In conventional ships, the main engine provides the power for the propeller, and additional engines, called gensets, are used to cover auxiliary power needs. In hybrid propulsion ships, however, the main engine and the gensets are connected and can work together to meet the ship's overall power requirements. Extensive optimization is required to determine the direction and amount of power flow between these two components so that all engines can be operated at the optimum operating point to save fuel. In addition to optimizing the route and the power management system, other factors have to be considered, such as replacing the Fixed Pitch Propeller (FPP) with the Controllable Pitch Propeller (CPP) and optimizing the engine control parameters depending on the operation. In many previous studies, different optimization methods have been investigated, albeit each of them only deals with one of the above topics at a time. Analytical optimization of the entire system is practically impossible due to the difficulty of describing the problem in mathematical terms and/or due to the large number of discrete parameters that must be considered and adjusted as part of the optimization. Moreover, since the optimization result for each given time step affects the system's future behavior, the degree of nonlinearity of the problem increases exponentially. Therefore, one of the most commonly employed methods in this field is Dynamic Programming, which has been used in several route optimization and EMS control studies. Dynamic Programming is a powerful and safe method that provides more degrees of freedom for optimizing problems compared to other methods where time steps are interdependent and future dependency of previous steps must be considered. Dynamic Programming often provides a way to overcome the burden of high overall problem complexity. Thus, if the problem is formulated adequately, Dynamic Programming solutions always represent a global optimum. However, DP-based methods require high computational power and large memory storage capacities. The presence of computational constraints poses a significant challenge and, with respect to optimizing the operation of a maritime vessel, prohibits the realization of optimization schemes that consider multiple operational aspects simultaneously (in parallel). In fact, the need to remain within feasible computation limits necessitates simplifications even in cases where only individual operational aspects are optimized. The present thesis aims to explore the potential of fuel saving in the maritime sector by adopting a comprehensive approach that focuses on the synchronized optimization of multiple crucial factors. Specifically, this research investigates the combined effects of using advanced technologies, such as wind propulsion systems and CPP, along with the synchronized optimization of route selection and energy management system control on the potential to enhance fuel efficiency for marine vessels. The core hypothesis of this study posits that by concurrently aligning and optimizing these diverse aspects, a synergistic effect will be achieved, leading to significant reductions in fuel consumption and carbon emissions. Synchronized route optimization, as proposed here, involves identifying the most fuel-efficient pathways under consideration of real-time data pertaining to weather conditions, sea currents, and vessel performance characteristics. By closely coordinating EMS control with route optimization, energy consumption on board can be intelligently managed, ensuring optimal energy utilization per the vessel's operational requirements. Additionally, integrating fine-tuning engine control parameters and CPP technology enhances propulsion efficiency, complementing the overall synchronized optimization strategy. The findings of this thesis are expected to shed light on the substantial fuel saving benefits attainable through the coordinated approach, thus providing directions for the maritime industry toward an environmentally sustainable operational practice. In view of the complexity associated with the problem of optimizing the operation of a maritime vessel, this thesis focuses on an optimization method based on machine learning, namely Reinforcement Learning (RL). In contrast to DP-based methods, RL-based methods are model-free methods. This fact allows RL to cope with a much higher level of complexity. In particular, the nature of RL lends itself to consider all operational aspects mentioned above in parallel. This includes simultaneous route optimization, energy management systems, and more. Using conventional methods, the concurrent handling of multiple optimization aspects is impossible simply due to the significantly higher computational power and memory requirements and due to the fact that the overall control system is not a Linear Time Invariant (LTI) system. In addition, other factors, such as the impact of CPP technology, the optimization of the engine control parameters, and the application of wind propulsion systems, can be gradually considered and included in the optimization scheme. Since RL-based optimization solutions emanating from model-free methods are not necessarily optimal in an analytical sense, this thesis also pursues the idea of enhancing the purely RL-based solution in a post-processing step using DP-based optimization to fine-tune certain operational aspects. A dedicated benchmark procedure is applied to compare, assess, and quantify the benefits of various optimization schemes, including conventional ones. In summary, this thesis explores and highlights the physics, the possibilities, and the limitations of conventional methods. It describes the machine learning approach and examines the hypothesis employing exemplary optimizations. Finally, the approach's robustness, capabilities, and limitations are discussed in detail. In Section 1.2, the objectives of this work are described in more detail.

## 1.2 Main Objectives

This thesis deals with the holistic operational optimization of a maritime vessel using an approach based on machine learning principles, namely RL. The advantages of RL over conventional methods and the significance of these advantages for the present application are described in detail in Section 2.3. To get a frame of reference for all subsequent investigations, in an initial step, the optimization of the route itself (without any consideration of other aspects) is investigated. Subsequently, the approach's complexity level is gradually increased, considering additional aspects, such as the replacement of FPP by CPP, the introduction of wind propulsion systems, and the optimization of engine control parameters. One of the most significant steps in this thesis is the investigation of the concurrent optimization of the route and EMS control system with and without consideration of other factors. For each of these aspects, the focus is on analyzing how the parallelization of the optimization brings an advantage. Accordingly, approaches are leveraged that lend themselves to perform all optimizations in parallel or in series. Of particular interest is the question of whether the consideration of additional aspects in the overall fuel optimization problem influences the selected route. Several transportation scenarios are considered and optimized in this sense. As an important part of this thesis, a comprehensive comparison of the applied approach with conventional methods will be performed. In this respect, a benchmark of different methods will be developed and evaluated in terms of limitations and accuracies. In addition, in order to achieve a more global optimum and, thus, maximum fuel economy, best practices involving a combination of the proposed machine learning method with conventional methods are presented and discussed. The objective of this thesis can be summarized as follows:

- Perform a literature review to get an overview of previous methods.
- Modeling all subsystems, such as the main engine, battery, gensets, flettner rotor, wingsail, CPP, etc.
- Configuration of a hybrid powertrain and implementation of this model in an RL environment.
- Development of a methodology for the implementation of route optimization in the RL environment.
- Set up an RL environment that allows simultaneous and separate optimization of different aspects, such as route, EMS control, engine parameter, pitch and engine speed, and consideration of wind propulsion system in terms of fuel consumption or cost.
- Application of different RL concepts, namely Deep Q-Network (DQN), Deep Deterministic Policy Gradient (DDPG), and Proximal Policy Optimization (PPO) and selection of the most suitable RL method for this application.

- Execution of different scenarios for parallel and serial optimization of various aspects.
- Evaluation of the influence of parallelization (increased complexity level) on the overall results.
- Detailed evaluation of Agent's actions concerning main engine and propeller efficiency.
- Developing a benchmark for the conventional methods with the novel approach introduced in this work and performing a detailed comparison between all methods.
- Introduce and discuss best practices to achieve the highest possible fuel savings, i.e., practices involving a combination of the conventional methods with the proposed RL method.

Figure 1.1 presents a graphical abstract of the thesis. This thesis is organized into dedicated chapters as follows: Firstly, the present chapter expounds upon this thesis's motivation and clear-cut objectives. Following this, a meticulous and exhaustive literature review on various relevant topics is conducted in Chapter 2, providing a comprehensive understanding of the existing body of knowledge. Moreover, in this chapter, the critical innovations introduced in this thesis are compared to the findings of previous studies, showcasing their pioneering contributions. Moving forward, this thesis delves into the core concepts of machine learning methods. A detailed explanation of these techniques is presented, providing a solid theoretical framework for the research. It serves as a crucial building block for the subsequent chapters. In Chapter 3, the comprehensive modeling of various constructive elements of the RL environment is thoroughly explained. Each aspect is methodically presented, offering insights into the intricacies of the RL approach adopted in this thesis. Chapter 4 presents the culmination of this work, showcasing the results obtained from the conducted research. A detailed evaluation of these results offers a deeper understanding of the findings' implications and significance. Finally, in Chapter 5, this thesis reaches its conclusive phase, summing up the essential findings and highlighting the crucial takeaways. Additionally, an outlook on future work is provided, pointing towards potential directions for further exploration and improvements in this field.

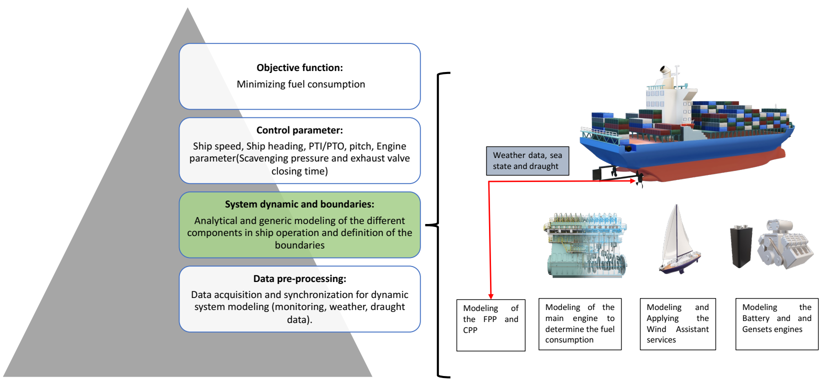


**Figure 1.1:** Graphical abstract of the thesis