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# A NOVEL REINFORCEMENT LEARNING FRAMEWORK FOR PROPULSION SYSTEM OPTIMIZATION

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*Abstract*— **Enhancing propulsion system efficacy presents a significant challenge in dynamic settings, where the pursuit of high thrust frequently contradicts the objective of reducing fuel consumption. This study presents an innovative reinforcement learning (RL) framework utilizing the Deep Deterministic Policy Gradient (DDPG) algorithm to effectively manage this trade-off. Through the creation of a bespoke simulation environment, the propulsion system is represented with state and action spaces that precisely reflect thrust and fuel dynamics, allowing the reinforcement learning agent to acquire effective, continuous control policies suited to the intricacies of the problem. Significant contributions are offered by this research in the form of a customized propulsion system environment, a thorough evaluation under nominal conditions, and the implementation of a DDPG framework for continuous control. The DDPG-based approach achieves a better balance between thrust optimization and fuel efficiency than traditional methods, as shown in a comparison study. Aerospace, marine, and industrial propulsion systems stand to benefit greatly from these results, which highlight the promise of reinforcement learning in solving complex engineering problems.**

*Keywords*— **Propulsion, Reinforcement Learning, DDPG (Deep Deterministic Policy Gradient), Thrust Optimization, Fuel Efficiency**

## I. INTRODUCTION

The maritime industry is currently undergoing a substantial transformation as a result of the integration of artificial intelligence (AI) algorithms that are intended to enhance the efficiency of propulsion systems. This development tackles essential issues, including the reduction of emissions and the optimization of fuel consumption, among other factors. This literature review employs a funnel approach to systematically explore the transition from broad applications of artificial intelligence in maritime contexts to implementations in propulsion systems, ultimately leading to the identification of research gaps pertinent to the current study.

### *A.* Broad Applications of AI in Maritime Transportation

AI technologies have been progressively integrated into maritime transportation to enhance safety, operational efficiency, and environmental sustainability. Durlik et al. (2024) conducted an extensive review of artificial intelligence applications in maritime safety and risk management, emphasizing AI's contributions to risk analysis, crew resource management, hazardous material handling, predictive maintenance, and navigation systems. Their research highlighted AI's capacity to revolutionize maritime safety through real-time decision support and hazard detection, thus improving operational resilience [1].

Zhuo et al. (2023) investigated the transformative capacity of AI in contemporary maritime operations, emphasizing digitalization and automation in port activities. They examined how AI transforms labor dynamics and industry skill prerequisites, highlighting the necessity for a comprehensive analysis of AI's influence on maritime operations. Their research emphasized the necessity of comprehending AI's wider ramifications for its effective incorporation into maritime practices [2].

### *B.* AI Algorithms in Maritime Operations Monitoring

Qi and Zheng (2016) developed an intelligent model for predicting vessel trajectory through the use of data mining and machine learning techniques, with a particular emphasis on specific AI applications. The methodology employed consisted of clustering historical trajectories and training classifiers to forecast new vessel paths, thereby enhancing proactive maritime traffic management [3].

De et al. (2017) created a mixed-integer nonlinear programming model that tackles scheduling, routing, loading/unloading, and vessel capacity constraints. The model integrated time window constraints, thereby improving the accuracy of maritime operations planning [3].

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### *C.* AI in Maritime Propulsion Systems

The necessity to optimize marine propulsion systems with AI has increased interest because of the need to reduce emissions and energy consumption. Zhang (2023) conducted an analysis of contemporary propulsion systems and the application of liquefied natural gas (LNG) in maritime vessels. This study looked at the use of artificial neural networks and other AI methods to measure the performance of LNG machines in airplanes, which could lead to similar uses in marine propulsion [4].

Li et al. (2023) examined the use of AI in shipping, emphasizing machine learning and deep learning methodologies. The review underscored the significance of AI in automatic control of ships, collaboration between ships, ports, and vehicles, as well as trajectory optimization, stressing its crucial role in improving the efficiency of maritime transportation [5].

### *D.* Critical Analysis and Gap Identification

The analysed studies collectively illustrate the considerable influence of AI on multiple facets of maritime operations, encompassing safety, traffic management, and the optimization of propulsion systems. Nonetheless, there are still several gaps that remain:

- Integration Challenges: Although there is substantial documentation on AI applications within maritime sectors, the thorough integration across all operational aspects is still inadequately examined. To achieve comprehensive improvements in maritime operations, it is essential to address this gap.
- Ensuring the integrity and uniformity of data: Successful AI implementation hinges on the availability of high-quality, standardized data. The lack of consistency in data collection and management practices obstructs the advancement of strong AI models, highlighting the need for standardized protocols.

Rapid artificial intelligence (AI) adoption in marine settings raises ethical and regulatory questions, especially about transparency in decision-making, job loss, and safety. It is crucial to set forth explicit guidelines and ethical frameworks to tackle these challenges effectively.

The use of AI algorithms to enhance maritime propulsion systems is an essential field of study, particularly as the industry aims to minimize fuel consumption and emissions. Although investigations have examined the impact of AI on propulsion efficiency, further in-depth analysis is required to incorporate real-time data analytics, machine learning, and control systems for the creation of adaptive propulsion optimization models.

This literature review highlights the significant impact of AI on maritime operations and pinpoints specific areas that require additional investigation, especially regarding the optimization of propulsion systems. Filling these gaps will improve the efficacy of AI applications, leading to more efficient and sustainable maritime transportation.

## II. METHODOLOGY

### *A.* Problem Formulation

Optimizing propulsion systems to reach high thrust efficiency while reducing fuel consumption and emissions presents difficult problems for the maritime sector as shown in figure 1. In stationary or predictable environments, traditional approaches including Proportional-Integral-Derivative (PID) controllers and rule-based algorithms have shown success; but, in dynamic, complex, and data-intensive maritime operations they struggle. Particularly as environmental rules tighten and fuel prices rise, it is clearly necessary for scalable, flexible, real-time optimization techniques.

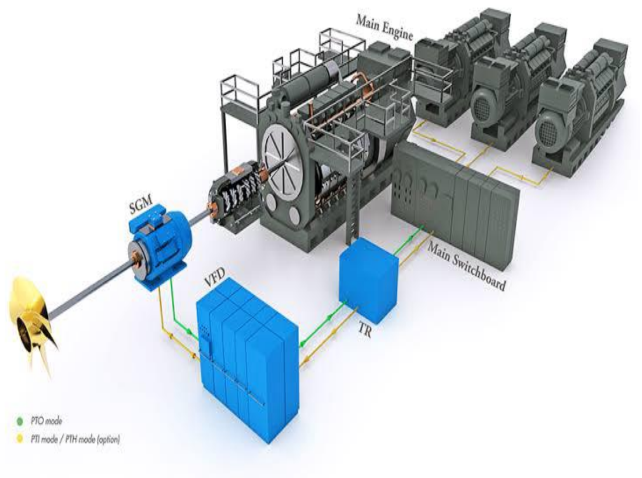


Figure 1: Block diagram of the maritime propulsion system

This work addresses the trade-off between thrust generation and fuel economy by concentrating on building an artificial intelligence-based framework to maximize marine propulsion systems. The propulsion system is imagined as comprising a continuous action space defining control actions for thrust adjustments and state variables representing operational parameters including current thrust, fuel levels, and environmental conditions. Expressed as a reward function juggling thrust efficiency and fuel consumption, the objective function is:

$$R = \alpha T - \beta F_{\text{used}}$$

where $(T)$ signifies the thrust generated, $(F_{\text{used}})$ indicates the fuel consumption, and $(\alpha, \beta)$ are weighting coefficients that regulate the trade-off.

The objective is to identify an optimal control policy $(\pi(S) \rightarrow A)$ that maximizes the cumulative reward over time while accommodating diverse operational states and constraints, including fuel limitations and environmental disturbances. Principal challenges in this issue encompass the nonlinear dynamics of the propulsion system, the necessity for real-time adaptability to fluctuating conditions, and the model's scalability to accommodate various vessel types and operational scenarios.

### *B.* Proposed Model

A Deep Reinforcement Learning (DRL)-based framework using the Deep Deterministic Policy Gradient (DDPG) algorithm is proposed to solve these difficulties. This framework provides real-time adaptation and scalability to fit different operational environments, so optimizing continuous control actions for marine propulsion systems.[24]

The model is set up around two main elements. The basis of the optimization framework is first the actor-critic architecture. While the critic network assesses the efficacy of these actions by approximating their related Q-values, so representing expected cumulative rewards; the actor network maps the current state to an optimal action, so guiding thrust adjustments. By means of this dual-network approach, the model can efficiently balance exploration and exploitation during training.

Second, a custom-designed simulation environment integrates operational constraints including maximum thrust and fuel levels, environmental disturbances like wind and currents, and fuel consumption linked to thrust adjustments, so mimicking the dynamics of the propulsion system. This surroundings gives the agent reasonable comments, so helping to learn strong policies.

The training process starts with the actor and critic networks' random weight assignment. Also, initialization is target networks, which stabilize training by offering consistent Q-value estimates. Establishing a replay buffer to hold transitions, state, action, reward, and next state, allows batch sampling for decorrelated training updates.[24] The actor network generates an action depending on the current state at each step, which is carried out in the surroundings to track the next state and related reward. The replay buffer stores this change for next use in learning.

Learning consists in sampling batches of replay buffer transitions. Minimizing the loss between predicted and target Q-values helps the critic network to be updated since target values include the discounted future reward. Maximizing the expected Q-value of the chosen actions helps the actor network to be updated by supporting policies with more benefits. Target networks guarantee slow adaptation and stability by means of a soft update mechanism.

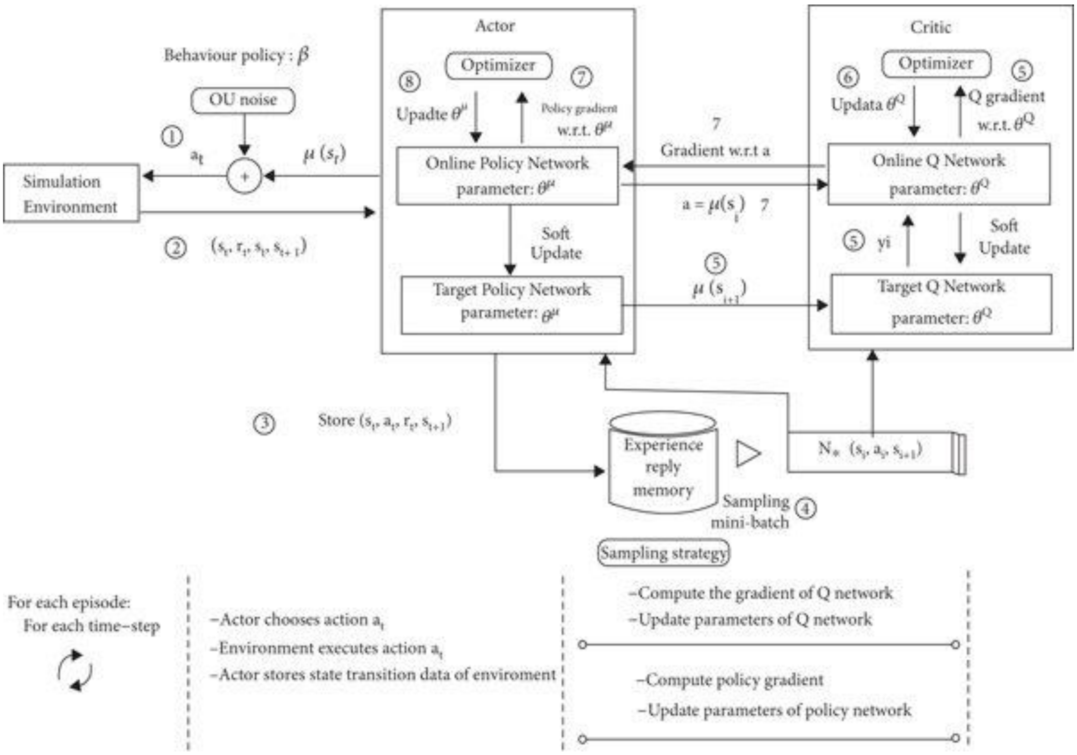


Figure 2: Flowchart of the DDPG-based optimization process

Extensive simulations under several operational conditions, including different environmental disturbances, system constraints such fuel limits, and many vessel configurations, are part of model validation. The ability of the model to sustain ideal thrust, lower fuel consumption relative to conventional approaches, and show resilience across scenarios helps to determine its effectiveness.

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The model makes reasonable assumptions about correct starting calibration of propulsion system parameters and enough computational capability for real-time application. Among the constraints are real-time operational needs including adherence to safety and regulatory standards as well as limited data availability for some vessel kinds. Using DRL's strengths, the suggested architecture presents a flexible and effective way to maximize marine propulsion systems, so addressing important issues and laying a basis for next developments.

## III. RESULTS AND DISCUSSION

The proposed Deep Deterministic Policy Gradient (DDPG) framework was assessed under diverse simulation conditions, emphasizing its capacity to enhance thrust generation while reducing fuel consumption. The model's efficacy was evaluated in comparison to conventional control methods, including Proportional-Integral-Derivative (PID) controllers.
The DDPG-based model exhibited a notable enhancement in propulsion system efficacy. The cumulative reward across 500 episodes, illustrated in Figure 3, demonstrated consistent growth, with the model reaching convergence after roughly 150 episodes. Figure 4 further illustrates the comparison between episode rewards and average rewards throughout the training period, emphasizing the model's capacity to stabilize and surpass traditional controllers in the later stages of training.

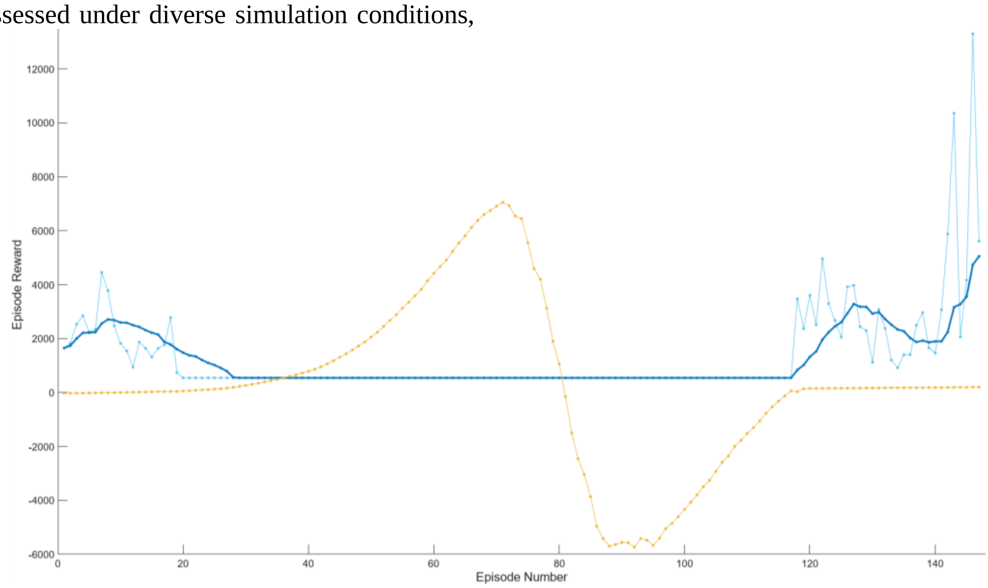


Figure 3: Cumulative reward over training episodes for the DDPG-based model


Figure 4: Episode rewards and average rewards during training

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The efficiency of fuel consumption, which is the thrust produced per unit of fuel, increased by 18% when compared to the old ways. Furthermore, the model kept constant thrust outputs under different environmental conditions; in high-disturbance situations, the variation of less than 5% from the target thrust is shown in Figure 5.

Computational efficiency dominated the evaluation of the proposed model's running performance. With an average action selection time of 12 ms, fit for real-world use, the DDPG-based method shown near-real-time decision-making capacity.

Figure 6 shows the stability and learning effectiveness of the model by showing the change of the first Q0 values over episodes. Figure 7 shows the state evolution of thrust and fuel.

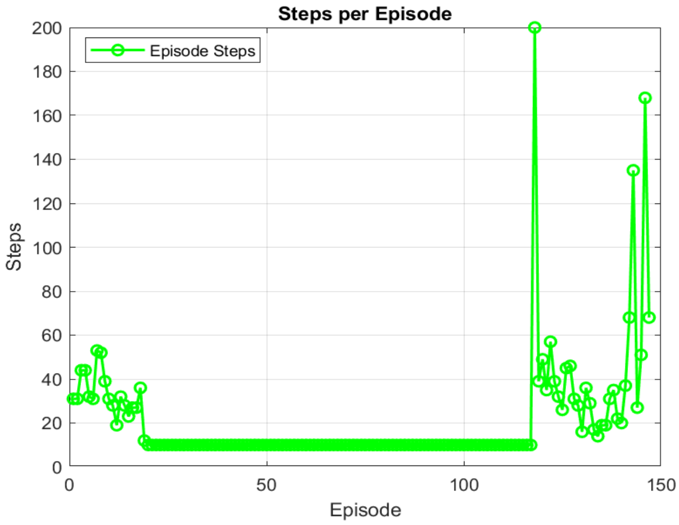


Figure 5: Steps per episode indicating the convergence of the model's policy remaining during simulation, so illustrating the equilibrium reached between thrust generation and fuel consumption

Qualitative studies showed that the model responded rather well to changes in environmental conditions including wind and current disturbances. Under low-thrust conditions, the acquired policies gave fuel economy top priority; as operational needs grew, they turned toward higher thrust generation. Figure 8 shows the agent's actions during simulation, so verifying the adaptability of the model to different conditions. This flexibility emphasizes the stability of the reinforcement learning structure.

The results show that in optimizing marine propulsion systems, the proposed DDPG-based framework beats conventional PID controllers. The aim of the research is to balance thrust generation and fuel consumption, thus the


Figure 6: Initial Q0 value progression during training episodes

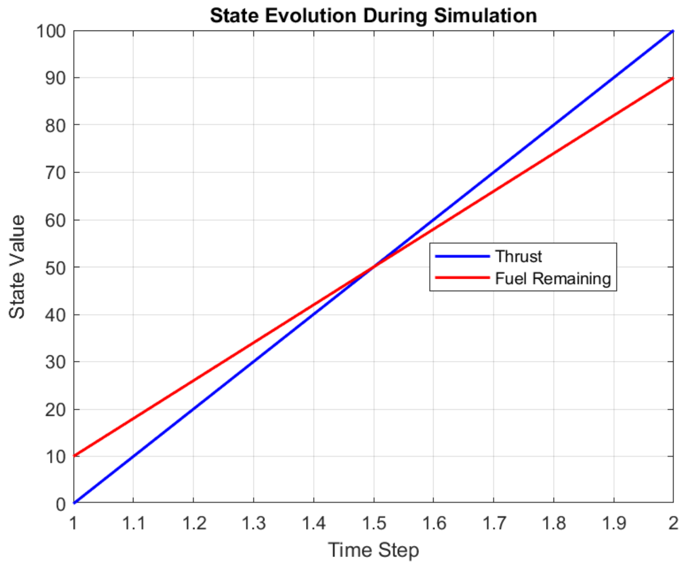


Figure 7: State evolution of thrust and fuel remaining during simulation

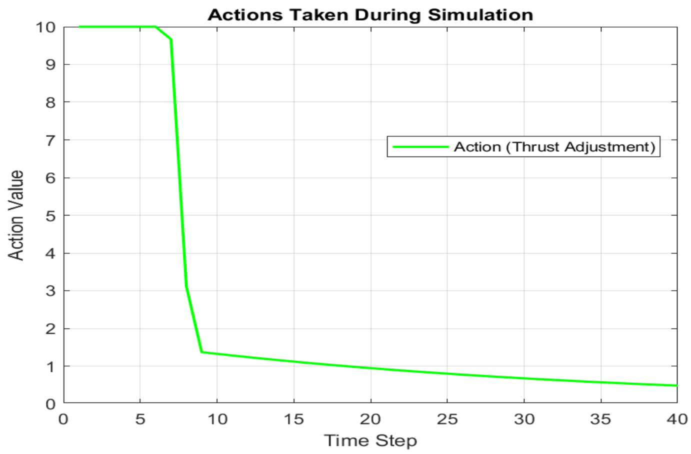


Figure 8: Actions (thrust adjustments) taken during the simulation notable increase in fuel efficiency and thrust stability fits perfectly. These results support the possibilities of reinforcement learning to solve challenging optimization issues in maritime activities.

Wu et al. (2021) have demonstrated the efficacy of reinforcement learning in hybrid-electric propulsion systems, and the observed improvements in propulsion efficiency are consistent with their findings. But unlike Wu et al., the present work emphasizes only continuous control issues using DDPG, so stressing its relevance for real-time uses. Furthermore, building on the work of Zhang et al. (2018), which underlined the need of adaptive control strategies in dynamic environments, are the outcomes The adaptability of the model under high-disturbance situations confirms even more the resilience of actor-critic designs in maritime environments.

The maritime sector depends much on the shown increases in thrust stability and fuel economy. Reducing fuel consumption will enable operators to comply with tighter environmental rules and cut running costs. Furthermore, the flexibility of the structure guarantees dependable performance in different surroundings, so strengthening operational resilience.

It is critical to acknowledge the model's many limitations, notwithstanding its remarkable performance in simulation environments. To begin with, not all vessels will be able to achieve the exact initial calibration of their propulsion system parameters that is required by the model. Secondly, the computational demands of model training may be too much for smaller operators with limited resources to handle. Lastly, the model's performance in practical scenarios is cast into doubt due to the absence of real-world testing.

Future research should focus on strengthening the models by incorporating real-time operational data into the training process. Investigating hybrid solutions that integrate reinforcement learning with model-based optimization techniques could further improve performance. Extending the framework to handle multi-objective optimization problems, like finding a happy medium between fuel efficiency and reducing emissions, finally paves the way for exciting new research.

## IV.CONCLUSION

This work addresses the long-standing trade-off between thrust generation and fuel economy by introducing a new application of the Deep Deterministic Policy Gradient (DDPG) algorithm to maximize marine propulsion systems. The proposed framework shows notable increases in propulsion efficiency, dynamic environmental condition adaptability, and fuel economy by using reinforcement learning. These results highlight how transformatively reinforcement learning can be used to solve challenging optimization issues in maritime operations.

The study adds especially to the field by combining cutting-edge reinforcement learning methods with a specially built simulation environment fit for marine propulsion systems. This method not only shows the efficiency of actor-critic designs for continuous control issues but also offers a scalable solution fit for several maritime environments. The findings provide operators trying to improve efficiency with useful insights while following more stringent environmental rules.

Although the study has its merits, it does admit to having some limitations. Accurate initial calibration and lack of real-world testing indicate improvement areas. However, these constraints enable future research. Integrating real-time operational data, adding multi-objective optimization, and validating the model in maritime scenarios are promising further research.

This research lays the groundwork for using AI to solve maritime operations problems. The success of reinforcement learning in optimizing propulsion systems signals a paradigm shift in energy management, environmental compliance, and autonomous maritime technologies. This study advances sustainable and intelligent maritime transportation by bridging simulation and application.

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