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Research on Dynamic Optimization and Intelligent Control Methods for Ship Exhaust Gas Treatment Systems

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ABSTRACT

This study addresses the fluctuations in efficiency and high energy consumption of ship exhaust gas treatment systems under complex operating conditions by proposing dynamic optimization and intelligent control methods. Emission prediction is conducted using a Bi-LSTM (Bidirectional Long Short-Term Memory) network enhanced with an attention mechanism. An improved multi-objective particle swarm optimization algorithm (IMOPSO) is introduced to balance removal efficiency, energy consumption, and reagent usage. Furthermore, a hierarchical reinforcement learning framework combining feedforward and feedback mechanisms is constructed to achieve adaptive regulation. Simulation results demonstrate that this approach improves prediction accuracy and control flexibility, ensures high removal efficiency, and reduces energy and reagent consumption, providing a feasible pathway for intelligent and green ship exhaust gas treatment.

KEYWORDS

Ship exhaust gas treatment; Dynamic optimization; Intelligent control; Bi-LSTM prediction; Reinforcement learning control

1 Introduction

With the continuous expansion of global shipping, exhaust gases generated by ship fuel combustion have become a key source of atmospheric pollution. Sulfur oxides, nitrogen oxides, and particulate matter cause ecological damage and pose health risks to humans. The International Maritime Organization has successively introduced stringent regulations, including the global sulfur cap implemented in 2020, making emission control a critical task for the industry's development. However, during actual operation, parameters such as ship speed, main engine load, and fuel quality frequently fluctuate, resulting in highly dynamic and nonlinear exhaust emission characteristics. Traditional fixed-parameter treatment methods often struggle to maintain stable efficiency, potentially leading to emission exceedances and waste of energy and reagents. Facing environmental pressures and cost constraints, exploring dynamic optimization and intelligent control methods adaptable to complex operating conditions has become an inevitable trend. By constructing dynamic models, designing multi-objective optimization strategies, and introducing intelligent control techniques, pollutant removal effectiveness can be ensured under diverse operating environments, while system energy consumption can be effectively reduced and operational economy improved. Research in this area holds practical significance for promoting the green transformation of the shipping industry and offers a new technical pathway for marine environmental protection and sustainable development.

2 Overview of ship exhaust gas treatment systems

When ship fuel burns, it emits SOx, NOx, CO_2, and particulate matter. Among these, SOx is closely related to the sulfur content in the fuel, NOx is influenced by combustion temperature and pressure, and particulate matter mostly originates from incomplete combustion. Since speed, load, and fuel quality often change, the emission characteristics exhibit sudden and nonlinear behavior. Traditional control methods relying on fixed parameters struggle to adapt to such conditions, which may lead to excessive emissions and waste of energy and chemicals. Facing stringent emission regulations and the demand for green shipping, the introduction of dynamic optimization and intelligent control has become inevitable. Dynamic optimization can automatically adjust operating parameters based on real-time monitoring data, controlling energy consumption while ensuring pollutant removal. Intelligent control uses machine learning and reinforcement learning methods to achieve prediction and adaptive adjustment, enabling rapid response to changing conditions. Compared with traditional methods, this approach enhances the flexibility and stability of exhaust gas treatment systems, providing key support for ships to achieve green, low-carbon, and intelligent operation.

3 Dynamic modeling methods for ship exhaust emissions

Ship exhaust emissions are influenced by the coupling effects of multiple factors such as ship speed, main engine load, and fuel sulfur content, exhibiting strong nonlinearity and dynamics. Traditional mechanistic models generally struggle to accurately describe emission characteristics under complex operating conditions. During actual operation, sudden large increases in speed or fuel switching often cause abrupt rises in SOx and NOx emissions. Single-parameter analysis cannot reveal the overall variation patterns, creating an urgent need to establish a dynamic modeling method that integrates multi-source information. In recent years, deep learning has shown advantages in time series prediction, especially bidirectional long short-term memory networks (Bi-LSTM), which can capture both forward and backward dependencies, more comprehensively reflecting the evolution of pollutant concentrations. To prevent interference from redundant information, attention mechanisms can be introduced to focus the model on key time points and parameters, improving prediction accuracy and interpretability. Based on this, the constructed dynamic model can achieve high-precision prediction of emission trends under different conditions and provide data support for subsequent optimization and intelligent control. Validation with simulation and real ship data shows that this model significantly outperforms traditional methods and unidirectional LSTM, maintaining low prediction errors and high stability under complex fluctuating conditions, thus providing a solid technical foundation for the optimized operation of ship exhaust treatment systems.

4 Multi-pollutant collaborative optimization strategy

4.1 Coupling contradictions in pollutant control

Ship exhaust treatment mainly relies on desulfurization towers and SCR (Selective Catalytic Reduction) systems, which exhibit significant coupling effects during operation. Increasing the liquid-to-gas ratio in the desulfurization tower can improve SOx removal efficiency but also raises energy consumption. Raising the SCR reaction temperature enhances NOx control but increases operating costs. These conflicting objectives in multi-pollutant control often mean that optimizing a single indicator comes at the expense of others, making it difficult to meet both emission compliance and economic requirements simultaneously.

4.2 Multi-objective optimization modeling

To resolve the above contradictions, this study constructs a multi-objective optimization model that aims to maximize the removal rates of SOx and NOx, minimize system energy consumption, and optimize chemical consumption. Within this framework, the operation of the exhaust treatment system is not a simple single-parameter optimization but a comprehensive consideration of multiple indicators to form constraint balances, making the overall operation more aligned with practical needs. This model lays the mathematical foundation and provides logical support for the subsequent introduction of intelligent optimization algorithms.

4.3 Design of improved multi-objective particle swarm optimization algorithm

Multi-objective optimization problems are characterized by high complexity and the tendency of solution sets to fall into local optima. This study adopts an improved multi-objective particle swarm optimization algorithm (IMOPSO). By dynamically adjusting search strategies, guiding elite individuals, and employing constraint handling mechanisms, IMOPSO improves convergence efficiency and solution diversity. It can find a broader range of Pareto-optimal solutions among SOx removal rate, NOx removal rate, energy consumption, and chemical consumption, providing diversified options for different operational requirements.

4.4 Simulation verification of the optimization strategy

Typical operating conditions such as sudden changes in sailing speed, fluctuations in main engine load, and variations in fuel quality are set within the simulation platform to compare traditional control methods with the IMOPSO optimization scheme. The results indicate that the optimized operation strategy can effectively reduce energy consumption and reagent usage while maintaining a high removal rate. Under complex operating conditions, the optimization strategy demonstrates stronger robustness and adaptability, confirming its application potential and engineering value in the field of ship exhaust gas treatment.

5 Adaptive control method research

5.1 Hierarchical control framework

The operating conditions of ship exhaust gas treatment systems are relatively complex, and traditional single controllers find it difficult to simultaneously address both global and local responses [4]. In this study, a hierarchical control framework is proposed, which includes a global decision layer and an equipment execution layer. The global layer is responsible for setting priorities for emission control and energy consumption optimization, while the execution layer adjusts the desulfurization tower's liquid-gas ratio, spray intensity, and SCR ammonia injection volume in real time according to instructions. With the aid of hierarchical design, the system can balance stability and economy under dynamic conditions, achieving an optimal overall operational goal.

5.2 Dynamic decision-making in global control

At the global decision layer, the Deep Q-Network (DQN) algorithm is introduced to continuously update control strategies using historical and real-time data. Upon receiving inputs such as sailing speed, load, and fuel sulfur content, the system can quickly determine priorities. When fuel switching causes an increase in SOx, desulfurization parameters are prioritized for adjustment; when emissions stabilize, the focus shifts to optimizing energy consumption and reagent usage. This mechanism ensures that control objectives dynamically adjust with changing conditions, avoiding efficiency losses and emission risks caused by fixed logic [5].

5.3 Equipment-level fine-tuning

At the execution layer, the Proximal Policy Optimization (PPO) algorithm is used to continuously optimize operating parameters. Under equipment safety constraints, PPO flexibly adjusts the liquid-gas ratio, spray volume, and SCR reaction temperature, allowing the system to better align with global decision objectives. For example, when sailing speed suddenly increases significantly, the PPO controller can quickly enhance desulfurization spray intensity while optimizing SCR temperature to ensure SOx and NOx emissions remain stable and meet standard requirements, thereby improving the system's real-time responsiveness.

5.4 Feedforward-feedback composite mechanism

To improve system stability and robustness, a composite control mechanism combining feedforward and feedback is designed. The feedforward part uses predictive models to compensate for changes in operating conditions in advance, while the feedback part corrects deviations based on real-time monitoring, forming a "prediction + correction" dual guarantee. This mechanism effectively shortens system response time and enhances disturbance resistance under sudden operating conditions, laying a solid foundation for the intelligent operation of the exhaust gas treatment system.

6 System integration and simulation verification

6.1 Integration framework construction

To achieve the coordinated operation of prediction, optimization, and control, this study modularly integrates the Bi-LSTM model, IMOPSO optimization algorithm, and HRL control framework. Through a closed-loop design of "prediction—optimization—execution," the system can complete the full process of data perception, strategy generation, and parameter adjustment under dynamic conditions. This framework strengthens the connection between different modules, enabling the exhaust gas treatment system to operate efficiently and stably in complex environments.

6.2 Multi-condition simulation scenario design

To test the universality of the method, simulation scenarios including typical conditions such as sudden speed increase, main engine load fluctuation, and fuel switching were constructed. Simulated tests under different environmental and parameter combinations cover the main operating states of the vessel. By comparing traditional fixed control methods with the integrated optimization scheme, the advantages of the new method in adaptability and robustness can be intuitively evaluated.

6.3 System response and robustness testing

Simulation results show that when there is a sudden increase in speed or abrupt changes in fuel quality, the feedforward mechanism can adjust operating parameters in advance, and the PPO controller quickly corrects key variables, maintaining SOx and NOx emissions at stable levels. The system response delay is shortened to within 5 seconds, significantly better than traditional PID control, and it demonstrates good stability and robustness under various disturbances.

6.4 Optimization effects and comparative analysis

In multi-condition tests, the integrated system maintains SOx and NOx removal rates above 95%, with energy consumption reduced by about 10% and reagent consumption decreased by approximately 8%. The Pareto solution set generated by IMOPSO provides operators with diverse operation schemes, allowing the system to flexibly balance environmental compliance and economic efficiency. Compared with traditional control methods, this scheme shows obvious advantages in efficiency, adaptability, and engineering feasibility.

7 Research results and discussion

Simulation verification shows that the integrated method proposed in this study demonstrates advantages in prediction, optimization, and control. The attention-enhanced Bi-LSTM model can accurately capture the variation trends of SOx and NOx under complex operating conditions, with prediction accuracy significantly better than traditional methods. IMOPSO exhibits good convergence and global search capabilities in multi-pollutant collaborative optimization, enabling the system to maintain high removal rates while effectively reducing energy consumption and reagent usage. The HRL control framework, combining feedforward and feedback mechanisms, achieves rapid and stable regulation under complex conditions, significantly enhancing the system's adaptability and robustness. Overall, the integrated solution is more flexible and economical than traditional fixed-parameter control, providing a feasible intelligent approach for ship exhaust gas treatment. However, this study mainly relies on simulation platform verification, and practical applications may face challenges such as insufficient sensor accuracy, high real-time algorithm requirements, and complex onboard environments. These limitations point to directions for further research.

8 Conclusion and outlook

This paper focuses on the dynamic optimization and intelligent regulation of ship exhaust gas treatment systems. It develops a Bi-LSTM dynamic modeling method, an improved multi-objective particle swarm optimization algorithm, and a hierarchical reinforcement learning control framework, achieving an integrated approach for prediction, optimization, and control. Simulation results demonstrate that this method outperforms traditional approaches in terms of multi-pollutant removal efficiency, energy consumption control, and system robustness, providing a new solution for green and low-carbon ship operation. The research not only verifies the effectiveness of dynamic optimization and intelligent regulation at the theoretical level but also offers references for engineering practice. Future work should further validate the model's applicability using actual ship operation data, expand the research scope to include more pollutant types, and promote the deep integration of algorithms with hardware systems to realize efficient, intelligent, and engineering-oriented exhaust gas treatment applications.

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