A Review of the Application of Simulation Technology in Maritime Logistics: A System Analysis based on Multi-Method Simulation

Youfeng Lu*

Business School, The Hong Kong Polytechnic University, Hong Kong, China

*1093845312@qq.com

Abstract

Maritime logistics, as a cornerstone of global trade, carries nearly 90% of international freight volume. However, traditional maritime logistics planning relies heavily on human experience and simplistic models, which limits its ability to address complex systems and real-world uncertainties. Simulation technology, with its advantages in virtual environment modeling and lowering trial-and-error costs, has become a valuable tool to solve these challenges. This paper systematically reviews mainstream simulation technologies in the field of maritime logistics and compares their application scenarios, advantages, and limitations. Based on this, it presents a multidimensional review of the practical impact of simulation on areas such as maritime network optimization, port operation efficiency, and supply chain integration. Furthermore, this study discusses current challenges faced by simulation technology and explores trends in its integration with emerging technologies such as digital twins. Finally, it proposes feasible future research directions, suggesting a focus on multi-technology integration to support the digital and low-carbon transformation of maritime logistics.

Keywords

Maritime logistics, simulation technology, digital twin, carbon emissions.

1. Introduction

1.1. Research Background

Shipping is an essential support for global trade and the upgrading of manufacturing industries. *Made in China 2025* [1] explicitly calls for the development of shipbuilding and marine engineering technologies to ensure the development and utilization of marine resources. In 2023, the global seaborne trade volume reached 12.292 billion tons, accounting for about 80% of international trade [2][3], highlighting its foundational role in the global economy [4].

As the core of global trade, maritime logistics is irreplaceable. It supports the circulation of the majority of international goods, ensuring the stability of the global economy. According to statistics, maritime transport carries nearly 90% of the world's traded goods [5], making it the artery of the world economy.

Under the Belt and Road Initiative [6] and *Made in China 2025* [1], the intelligence and efficiency of maritime logistics have become key aspects of national competitiveness. The global maritime market has maintained an annual growth rate of about 2% [7][8], showing steady development momentum.

1.2. Current Research Status

Despite continued growth, maritime logistics still faces challenges such as high costs, low efficiency, and rising carbon emissions. Heavy reliance on human experience results in inefficient scheduling and port congestion, and route planning lacks flexibility. Between 2016 and 2023, greenhouse gas emissions from ships increased by about 12%, posing a critical challenge for low-carbon transition [9]. Therefore, process optimization and emission reduction have become central research areas.

To address these issues, the industry typically plans more efficient shipping routes. Traditional maritime logistics planning often depends on human expertise or simple mathematical formulas, which struggle to provide accuracy and flexibility in complex systems. In contrast, simulation technology-already widely used in advanced industrial engineering and production management-has begun to permeate maritime logistics. By modeling shipping plans, operational processes, and management models in virtual environments, simulation offers decision-makers more scientific and effective solutions.

1.3. Significance of Simulation Technology

Simulation technology has great potential and practical value in maritime logistics. Theoretically, it overcomes the limitations of traditional optimization methods, especially in dealing with complex, dynamic systems. It enables repeated experimentation and optimization in virtual environments, reducing trial-and-error costs and providing accurate forecasts and evaluations.

In practice, many ports have adopted simulation technology. By optimizing loading and unloading processes, ports can significantly reduce vessel waiting times and lower empty load rates, thus increasing overall efficiency. For example, the Port of Rotterdam uses a digital twin system integrating IoT and simulation to model vessel dynamics and weather scenarios, saving approximately $80,000 daily and significantly reducing waiting times [10].

2. Classification and Principles of Maritime Logistics Simulation Technology

2.1. Classification of Simulation Types

Discrete Event Simulation (DES) is a commonly used simulation technique suitable for modeling systems driven by discrete events. In this approach, system state changes are triggered by events, each occurring at a specific point in time, thereby driving system evolution. In maritime logistics, DES is applied to cargo handling, transportation scheduling, warehousing, and other fields. For example, DES can effectively simulate vessel arrival times, container loading and unloading sequences, and resource scheduling and allocation. In such applications, ports can integrate resource planning to optimize operations and improve overall efficiency [11]. However, DES has limitations when it comes to continuous modeling, such as capturing nonlinear dynamics and handling complex interactions among continuous variables [12]. Hence, it is only applicable to event-driven discrete processes. The main categories of simulation technologies are as follows.

DES is suitable for analyzing and managing systems with discrete events, such as cargo handling processes at ports. System Dynamics (SD) is suitable for analyzing the long-term dynamic behavior of complex systems, such as supply chain network analysis and demand forecasting, but limited in capturing local details and accurately simulating individual behavior. Agent-Based Modeling (ABM) is used to study interactions and collective behavior among individual agents, such as vessel navigation and AGV (Automated Guided Vehicle) transportation. However, since each agent acts independently, it requires large computational resources. Numerical Simulation (NS) is mainly used to model physical processes by discretizing mathematical models and performing iterative calculations to simulate system dynamics. It is widely used to assess vessel safety under different conditions, but requires significant computational resources to handle complex scenarios with high precision.

In summary, various simulation methods have different focuses in maritime logistics. DES focuses on modeling changes occurring at discrete time points. SD is suitable for analyzing long-term macro-scale behavior. ABM excels at studying micro-level interactions driving macro-level phenomena, and NS is well-suited for evaluating and analyzing various configurations under different scenarios.

2.2. Key Principles

2.2.1. DES

DES is based on an event-driven mechanism to model changes in system state, which is updated with each triggered event. In this model, the conditions of an event determine its triggering sequence. The system state during this process can be expressed by the following formula.

$$S(t_{next}) = S(t_{current}) + \Delta(S, e)$$

where $S(t_{next})$ represents the system state after the current event has been processed; $S(t_{current})$ represents the system state at the moment the event is processed;

$\Delta(S, e)$ represents the state change caused by event e.

This formula indicates that the simulation system is driven by a series of discrete events. When no event occurs, the system state remains unchanged, and since events occur at discrete time points rather than continuously, the system state is also not continuous.

2.2.2. SD Simulation

SD simulation is a technique used to model continuous systems, where the continuous change of system states is obtained through differential equations. In this model, the rate of change in stock variables is determined by the inflow and outflow rates of the system, and this process can be expressed by the following equation.

$$Stock(t) = \int [NetInflowRate(\tau)]\, d\tau + Stock(t_0)$$

Where, $Stock(t)$ represents the system stock level at time t; *Net Inflow Rate* represents the net inflow rate, i.e., the difference between all inflow and outflow rates.

This formula shows that the system is a continuous process driven by feedback loops, and the system state changes at every moment based on the relationships between different flow rates. Therefore, this simulation method is suitable for long-term macro-level trend analysis, such as epidemic transmission and other complex problems.

2.2.3. Agent-Based Simulation

Agent-based simulation is based on the interactive behavior of autonomous agents to model complex systems. System state is updated through parallel interactions and actions performed by all agents. In this model, each agent makes independent decisions based on its own rules and its perception of the environment. The process can be represented as follows.

$$GlobalState\,(t+\Delta t) = A_1(t+\Delta t), A_2(t+\Delta t), \ldots, E(t+\Delta t)$$
$$A_{\mathrm{i}}(t+\Delta t) = F(A_{\mathrm{i}}(t), PerceivedState(t))$$

Where, *Global State* represents the system state at time t, composed of the states of all agents A_i and the environmental state E. The function F defines the behavior rule of agent i, and the new state of each agent is determined by its previous state and its perception of the environment and other agents.

2.2.4. NS

NS is based on time-stepping to model the evolution process of continuous systems, where the system state is updated at artificially discretized time intervals. In this model, the time step determines the computational sequence of the state, and the system state during this process can be represented by the following formula:

$$S(t_{i+1}) = S(t_i) + F(\,S(t_i),\, t_i\,) \times \Delta t$$

Where, $S(t_{i+1})$ represents the system state at the next time step; $S(t_i)$ represents the system state at the current time step; $F(S(t_i), t_i)$ is the differential equation or function describing the rate of change of the system state;

Δt denotes the fixed time step length.

This expression shows that numerical simulation is a method used to obtain approximate solutions for continuous dynamic systems. The system state is updated at every time step, requiring a sequence of discrete time points to approximate continuous change. This computational method is widely applied to physical field problems such as computational fluid dynamics.

2.3. Comparative Analysis

Based on existing literature and application scenarios, a comparative analysis of various simulation types is conducted. With applicability, advantages and disadvantages, computational load, and real-world examples as reference criteria, a horizontal comparison is made to analyze the characteristics of the four simulation techniques mentioned above. The details are shown in Table 1.

Table 1. Comparison of Four Simulation Techniques

	Applicable Scenarios	**Advantages**	**Disadvantages**	**Computational Load**	**Example**
Discrete Event Simulation	Event-driven systems	Good at handling step-by-step event processing and stochastic processes; flexible modeling	Difficult to simulate continuously changing systems	Medium	Simulation of bank counter queuing system
System Dynamics Simulation	Macro-level dynamic systems	Can capture long-term trends and feedback mechanisms	Ignores individual heterogeneity	Relatively low	Simulation of interaction between urban population growth and resource consumption
Agent-Based Simulation	Heterogeneous agent interaction systems	Captures complex adaptive and self-organizing behaviors	Model development is complex, high computational cost	High	Simulation of ant colony foraging behavior
Numerical Simulation	Physical or engineering systems described by mathematical equations	Provides high-precision numerical solutions, suitable for continuous systems	High computational cost; sensitive to model simplification and grid design	High	Simulation of airflow around aircraft wings

3. Applications of Simulation Technology in Maritime Logistics

3.1. Maritime Network Optimization

In the context of intensifying global maritime competition, maritime network optimization has become a key factor in improving system efficiency and responding to uncertainties. Its core lies in achieving a balance between transportation cost and efficiency through rational route design, dynamic vessel scheduling, and node allocation. Facing network complexity, cost fluctuations, and weather-related external factors, optimization models require strong dynamic adaptability.

Existing studies have proposed various optimization methods for route design. Gu et al. established a non-strict hub-and-spoke network model to reduce computational complexity and respond to market fluctuations[13]. Wang optimized shipping routes based on ocean current characteristics, effectively reducing fuel consumption [14]. Chen proposed a hub-and-spoke maritime network model to alleviate vessel scheduling issues caused by hub port congestion[15].

In terms of simulation applications, Discrete Event Simulation has been used for vessel berthing and loading/unloading optimization. Feng et al. demonstrated through simulation experiments that flexible speed adjustment can improve resource utilization and reduce transportation costs by 10%–20% [16]. Agent-based simulation has been used to model interactions between ports and vessels. The multi-agent system built by Yu et al. showed that average vessel waiting time at ports is negatively correlated with the level of system coordination [17].

3.2. Port Operation Efficiency

Ports are critical nodes in maritime logistics systems, and their operational efficiency directly affects the cost and time of the entire transportation process. With increasing volumes of bulk cargo and container throughput and growing pressure on port capacity, efficient port operation depends not only on good resource allocation but also on scientifically organized handling procedures. Improving port operational efficiency has long been a key research focus in the maritime logistics field.

Many studies in the literature focus on how to use simulation technology to improve port operation efficiency, especially in optimizing cargo handling processes, resource allocation, and distribution. Simulation models offer significant advantages in this regard. For example, Cai et al. adopted an ontology-based modeling method to analyze implementation pathways for port simulation technology [18].

System Dynamics Simulation and Numerical Simulation are widely used in port resource allocation. System Dynamics can simulate dynamic changes in port resources, predict bottlenecks based on real operational conditions, and provide optimization strategies. By modeling dynamic logistics processes, decision-makers can evaluate solutions without real-world experiments. For instance, Xu et al. conducted a dynamic simulation analysis of a diesel engine timing chain transmission system [19].

Numerical Simulation is generally used in port loading/unloading processes and storage yard layout optimization. By simulating different yard configurations, it can reduce unnecessary transport distances.

3.3. Supply Chain Integration

Modern maritime logistics has evolved from a single transport process into a multilayered global supply chain system involving multiple transport modes, cross-border tariffs, and other dynamic factors. Its efficiency and cost directly affect enterprise competitiveness and supply chain optimization.

With accelerating information technology and globalization, simulation technology has played an increasingly important role in supply chain integration. Agent-based simulation and hybrid simulation are widely used to analyze interactions of logistics and information flow among supply chain nodes. Research shows that simulation-based optimization can significantly reduce transportation costs, improve delivery timeliness, and increase inventory turnover efficiency. For example, Xia used simulation to optimize global supply chain operation strategies under external shocks, providing references for predicting exogenous impacts for both enterprises and governments [20].

Agent-based simulation can model dynamic interactions among manufacturing, warehousing, and retail nodes to evaluate system stability under demand fluctuations and transportation disruptions. Hybrid simulation, on the other hand, is used to optimize supply chain network design and enhance system adaptability in complex environments.

3.4. Environmental Impact Assessment

Meanwhile, the shipping industry is also one of the major sources of global greenhouse gas emissions, and its carbon emissions have gained international attention. To address this challenge, the Chinese government has issued policies to ensure carbon peaking by 2030 [21] and has gradually introduced environmental regulations. In this context, simulation technology can play an important role by providing scientific evidence for emission reduction strategies.

Many studies have begun to focus on carbon emissions in the maritime industry, especially on micro-level issues such as fuel selection, vessel design, and voyage optimization. For example, Zheng et al. used simulation models to study the impact of different excess air coefficients and ignition timings on maritime carbon emissions. The results showed that the lowest carbon emissions occurred when the excess air coefficient was 2.0 and the ignition timing was -20° [22].

Numerical simulation technology is also widely applied to carbon emission research, enabling simulation of emissions from different fuel types across different voyage distances and vessel types, thereby helping shipping companies select environmentally friendlier fuels. Meanwhile, system dynamics can effectively analyze the long-term effect of policy and economic factors on shipping carbon emissions under dual pressures.

4. Simulation Tools and Technical Platforms

In the field of maritime logistics simulation, selecting appropriate tools is essential to ensure effective modeling and reliable simulation outcomes. Different simulation tools have distinct features and advantages, making them suitable for different application scenarios.

4.1. Overview of Mainstream Tools

Currently, the most commonly used simulation tools in maritime logistics include AnyLogic, Arena, and FlexSim.

AnyLogic is a multi-method simulation software that supports discrete event simulation, system dynamics, and agent-based modeling. It enables seamless integration of different modeling approaches and is suitable for systems with complex dynamic interactions and feedback mechanisms. In the study conducted by Xu, AnyLogic was used to simulate emergency medical dispatch during the 2014 Kaohsiung gas explosion accident [23].

Arena is mainly applied to process optimization and statistical analysis. It performs well in scenarios such as cargo transportation, port terminal operations, and vessel scheduling, but has limited capability in dynamic system modeling and agent behavior simulation.

FlexSim excels in 3D discrete event simulation and is widely used in logistics, manufacturing, and warehouse optimization. It provides strong visualization and dynamic monitoring functions but lacks flexibility in highly customized modeling.

In summary, AnyLogic is better suited for complex multi-dimensional systems, while Arena and FlexSim are more appropriate for process-level optimization and efficiency analysis.

4.2. Technological Development Trends

The development of simulation technology is not only reflected in the iteration of tools themselves, but also in the integration of simulation with emerging technologies. With the rapid advancement of artificial intelligence, big data, and digital twin technologies, intelligent simulation has become the major direction of future development. These technologies enhance the intelligence level of simulation models and enable new approaches to solving more complex maritime logistics problems.

The integration of artificial intelligence and big data is an important trend in current simulation research. By applying machine learning and deep learning algorithms to simulation, systems are able to extract patterns and make predictions from massive historical and real-time data, automatically adjusting simulation model parameters. For example, Liu et al. improved short-term power load forecasting models using artificial neural networks [24]. AI can also combine weather data, traffic conditions, and port traffic flow to improve operational efficiency and system reliability. Meanwhile, big data enhances the accuracy and credibility of simulation results by providing richer underlying datasets.

Digital twin technology provides a new perspective for simulation. By building a virtual model that mirrors the physical system in real time, it enables monitoring of equipment conditions and operational processes. For example, Shanghai Yangshan Port applies digital twin technology to monitor container stacking and loading/unloading progress, allowing prediction of system bottlenecks and optimization of workflows [25].

5. Challenges and Future Development Directions

Although simulation technology has made significant progress in maritime logistics, it still faces numerous challenges in areas such as data acquisition and modeling complexity. As demand for simulation continues to grow, overcoming these challenges and improving simulation accuracy and efficiency have become focal points of current research.

5.1. Data and Modeling Challenges

Maritime logistics simulation depends on large volumes of real-time, high-quality data; however, in practice, it often encounters problems such as incomplete data, data scarcity, and a lack of standardization, which impair model accuracy and the reliability of decisions. Data gaps mainly arise from technological limitations, access restrictions, cost constraints, and barriers to cross-stakeholder collaboration, with data from remote routes or specialized transport operations being particularly scarce. The absence of unified formats across different companies and platforms also complicates data integration.

The modeling phase is heavily affected by multivariate uncertainty, and traditional methods struggle to cope with dynamic environments. As data scale and complexity increase, computational resources become a bottleneck. To address these issues, improvements can be made via data cleaning and machine learning: the former enhances data quality through inspection, interpolation, and standardization; the latter uses historical samples to predict missing values and extract latent patterns, thereby increasing model adaptability and accuracy.

5.2. Technology Integration

To address challenges in data acquisition, modeling, and computation, simulation technology is evolving toward multi-method integration, primarily reflected in two aspects, hybrid simulation and the combination of agent-based simulation with machine learning.

Hybrid simulation is capable of handling both discrete events and continuous dynamic processes. Discrete event simulation is suitable for modeling sudden operations and resource scheduling, while system dynamics simulation excels in depicting continuous feedback and cumulative effects. By integrating both methods, complex system evolution can be represented more comprehensively. For example, Helal proposed a hybrid modeling framework that integrates discrete event simulation with system dynamics to simulate manufacturing enterprise systems in dynamic environments [26].

Combining agent-based simulation with machine learning enables the optimization of individual decision-making through algorithmic learning. Agents can adjust behavior strategies based on past experience and environmental feedback, improving the realism and adaptability of system simulations.

Future research may incorporate multi-objective genetic algorithms, particle swarm optimization, and other intelligent optimization methods, such as grey wolf and whale optimization algorithms, into simulation processes to enhance computational efficiency and support intelligent decision-making.

5.3. Application Expansion

The application of simulation technology in maritime logistics is rapidly expanding, covering areas from unmanned vessel operation and automated terminals to the construction of intelligent logistics supply chains. As automation technologies mature, more ports are deploying automated systems, and simulation is used to evaluate their feasibility and efficiency in advance. The safety and decision-making abilities of unmanned vessels in complex navigation environments can also be validated through simulation. Intelligent logistics networks leverage real-time data collection and analysis to optimize efficiency across all stages, from warehousing to transportation hubs.

Simulation technology also demonstrates strong practicality in cross-industry applications. For example, in emergency logistics, simulation can optimize the efficiency of material transport, assess route accessibility, and enhance multimodal coordination.

Future applied research should focus on: real-time simulation and dynamic adjustment, achieved by integrating Internet of Things (IoT) technologies for real-time data input and system adaptation; virtual reality (VR) and augmented reality (AR), which provide immersive training experiences for high-risk operations, improving safety; cloud-based simulation and high-performance computing, which address the limitations of computational resources and support the simulation of complex models.

6. Conclusion

6.1. Summary of Current Research

This paper provides a systematic review of the application status, key technologies, and future development prospects of simulation technology in the field of maritime logistics. Simulation technology has been widely applied in maritime logistics, demonstrating significant effectiveness in areas such as route optimization, port operations, supply chain integration, and environmental assessment. By analyzing the main simulation methods, including discrete event simulation, system dynamics simulation, and agent-based simulation, this study highlights the respective advantages and limitations of each technique in maritime logistics. For instance, discrete event simulation is highly effective for analyzing discrete events in ports, such as cargo loading and unloading, system dynamics simulation is suitable for macro-scale dynamic analysis, while agent-based simulation excels in modeling complex interactive systems.

Simulation technology has already achieved substantial progress in key areas such as route optimization, leading to improved transportation efficiency, optimized resource allocation, and reduced operational costs. Simulation-based optimization can currently achieve 10%–20% cost savings in transportation, along with significant improvements in operational efficiency. However, the field continues to face challenges, particularly in data acquisition and modeling complexity. There remains considerable room for improvement in areas such as data cleaning and the integration of machine learning.

6.2. Future Research Priorities

Based on the current state of research, future studies may focus on the following directions.

(1) Promoting multidisciplinary technology integration is essential. Strengthening the integration of various simulation methods, such as discrete event simulation and system dynamics simulation, with emerging technologies like artificial intelligence and digital twins will enhance model accuracy and applicability, thus improving the ability to address the diverse demands of complex systems.

(2) Real-time dynamic simulation research is also critical. By leveraging sensor data and the IoT, real-time simulation systems capable of dynamically responding to environmental changes can be developed. This is particularly important for scenarios involving uncertainty, such as emergency events or adverse weather conditions.

(3) In terms of intelligent applications, research may focus on emerging scenarios such as automated ports. Simulation environments developed based on these applications can also expand their influence across the entire intelligent logistics supply chain.

(4) Green shipping simulation assessment urgently needs to be strengthened. In response to carbon emission policies, factors such as the use of low-carbon fuels and carbon capture technologies should be incorporated into simulation models to support the industry's goal of achieving carbon neutrality and to promote the sustainable development of maritime logistics.

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