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Optimizing Green Supply Chains and Sustainable Cities Using Deep Reinforcement Learning

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Abstract. This study aims at exploring the cost control method of green supply chain based on deep reinforcement learning, and studying its application in building green and low-carbon cities. Firstly, the concept and background of deep reinforcement learning and green supply chain cost control are introduced. Then, a cost control method of green supply chain based on deep reinforcement learning is proposed, including green supply chain modeling, the application of reinforcement learning in green supply chain and the strategy by using deep reinforcement learning to optimize cost control.

Keywords: Deep reinforcement learning; Green supply chain; Cost control; Green and low-carbon cities

I. Introduction

With the global environmental problems become increasingly prominent and the sustainable development is urgently needed, green supply chain management and the construction of green and low-carbon cities have become an important research field. As one of the core issues of green supply chain management, cost control of green supply chain is of great significance for enterprises to achieve sustainable development goals. However, traditional supply chain cost control methods often fail to take environmental factors and carbon emissions into full consideration, resulting in poor effect of green supply chain management (Xiao et al., 2023). In recent years, as one of the important research directions in the field of artificial intelligence, deep reinforcement learning has strong modeling and optimization capability, and has shown unique advantages in solving complex problems and optimizing decisions. Therefore, it is expected to improve the efficiency and environmental sustainability of supply chain management to apply deep reinforcement learning in green supply chain cost control.

On the other hand, with the accelerating urbanization process, the construction of green and low-carbon cities has become an important task for governments and cities managers. The construction of green and low-carbon cities involves transportation, energy, waste and other fields, which requires comprehensive consideration of the utilization of different resources and environmental protection (Zhang et al., 2023). On this background, deep reinforcement learning, as a powerful intelligent optimization method, provides new possibility for the construction of green and low-carbon cities.

2. Related overview

2.1 Overview of deep reinforcement learning

Deep reinforcement learning is an important branch of machine learning and artificial intelligence. It combines the techniques of deep learning and reinforcement learning, aiming at realizing that the intelligent system learns and optimizes decision strategy by interacting with the environment. Deep learning uses deep neural network model to train and learn with a large amount of data, which can effectively capture complex features and patterns of data. However, reinforcement learning gradually optimizes decision-making strategy through trial-and-error learning through the interaction between intelligent agent and the environment to maximize cumulative rewards (Zhao et al., 2023) (Wang & Shen, 2023).

The core of deep reinforcement learning is the combination of deep neural network and reinforcement learning algorithm. Deep neural network, as function approximator, can learn and represent complex state and action space. It can process high-dimensional input and output effectively through the combination of multi-layer neurons and nonlinear transformation. The reinforcement learning algorithm is responsible for training the deep neural network, and gradually optimizes the parameters of network through exploration and utilization, so that the intelligent agent can make the optimal decision. Deep reinforcement learning has shown great potential in many fields. For example, in game field, deep reinforcement learning has triumphed over top human players in complex games such as go, chess and poker. In the field of autonomous driving, deep reinforcement learning can learn to control a vehicle and make safe and efficient decisions (Hart et al., 2023) (Xia et al., 2023). In the fields of natural language processing and machine translation, deep reinforcement learning can realize the tasks, such as intelligent conversation and language understanding.

By combining the advantages of deep learning and reinforcement learning, deep reinforcement learning can learn and optimize decision-making strategies in complex environment, which has a wide application prospect. In this study, the application of deep reinforcement learning in the cost control of green supply chain and construction of green and low-carbon cities will be explored, to improve the effectiveness and efficiency of supply chain management and urban sustainable development (Zhang et al., 2023) (Liu Y. et al., 2023).

2.2 Overview of the cost control of green supply chain

Cost control of green supply chain refers to realizing environmental friendliness and sustainability of supply chain through reasonable control and cost reduction in green supply chain management. Traditional cost control of supply chain mainly focuses on the cost optimization of logistics, inventory, transportation and other aspects, while the cost control of green supply chain pays more attention to environmental factors and sustainable development. The goal of cost control of green supply chain is to reduce environmental impact and carbon emissions and improve resource utilization efficiency on the premise of ensuring efficient operation of supply chain. It involves the cost control of all links of the supply chain, including supplier selection, logistics, production process, product design and so on. Through the adoption of green procurement, energy conservation, emission reduction, waste recycling and other measures, it can reduce environmental cost, and improve the competitiveness of enterprises and brand image. The cost control of green supply chain faces a series of challenges and problems. Firstly, green supply chain involves multiple participants, which requires coordination and cooperation among all parties. Secondly, the cost control of green supply chain needs to consider the economic and environmental benefits comprehensively and balance the cost and benefits. In addition, the cost control of green supply chain needs to consider the characteristics and differences of different industries and regions, and formulate corresponding strategies and measures (Chen et al., 2023). In the research and practice, some methods and techniques have been proposed to support the cost control of green supply chain. For example, life cycle cost assessment methods can consider the life cycle cost and environmental impact of a product from production to retirement comprehensively. The optimization model and algorithm can help enterprises find the optimal cost control strategy in the case of limited resources. In addition, the development of information technology also provides support for the cost control of green supply chain, such as the application of the Internet of Things, big data analysis and other technologies (Azadi et al., 2023).

2.3 Urban Sustainable Development Overview

Urban sustainable development is a global research hotspot, covering theoretical and practical explorations in multiple fields. Scholars both domestically and internationally have conducted research on urban sustainable development, covering various aspects such as urban environment, economy, and society, delving into the depth of urban sustainable development from different dimensions.

In terms of urban environment, scholars focus on improving the efficiency of resource utilization and environmental quality in cities. Through perspectives like ecology and environmental science, they study the construction and management of urban ecosystems, explore the protection and restoration of urban ecological environments, as well as the sustainable development paths of environmental elements such as urban green spaces, water resources, and air quality. Additionally, issues like urban energy utilization and waste management have become research hotspots. Through technological innovation and policy guidance, efforts are made to promote the transformation of urban energy structures, reduce carbon emissions, and facilitate the establishment of circular economic models (Zhang et al., 2023).

Regarding the economy, research on urban sustainable development focuses on optimizing urban industrial structures and enhancing innovation capabilities. Strategies such as industrial upgrading and innovation-driven development are employed to promote sustainable economic growth in cities and increase employment opportunities. Meanwhile, cooperation and exchanges between cities have also become a research focus, exploring the economic complementarity and coordinated development between cities, and driving regional economic integration and sustainable development (Wang et al., 2023).

In the social aspect, research on urban sustainable development focuses on the quality of life of urban residents and social equity. By enhancing the levels of public services such as education and healthcare, efforts are made to improve the living conditions and happiness of urban residents.

Additionally, urban governance and social participation are also of great concern, exploring the improvement of urban governance systems and the establishment of democratic participation mechanisms to promote urban social stability and harmonious development (Xu & Wang, 2023).

3. Cost control method of green supply chain based on deep reinforcement learning

3.1 Green supply chain modeling

Green supply chain modeling is the first step of the cost control method of green supply chain based on deep reinforcement learning. By establishing an appropriate mathematical model, the key elements in the supply chain and their relationship can be described, providing input and reference for subsequent reinforcement learning algorithm.

Case: Modeling of a company's green supply chain

Suppose a company purchases raw materials from suppliers, and then sells the products to distributors after processing and manufacture. They eventually deliver the products to consumers. In order to realize the cost control of green supply chain, it is necessary to model each link of the supply chain.

Table 1. Raw material procurement

Link	Cost (unit: ten thousand yuan)	Carbon emissions (unit: ton)	Waste generation (unit: ton)
Supplier	10	100	5
Producer	20	150	10
Distributor	15	80	3

Total Cost = supplier cost + producer cost + distributor cost

Total Carbon Emission = supplier carbon emission + producer carbon emission + distributor carbon emission

Total Waste Generation = supplier waste + producer waste + distributor waste

A mathematical model of supply chain can be built by collecting and collating data of cost, carbon emission and waste output of each link in the supply chain. The formula in the model can be designed according to the actual situation to calculate indicators such as total cost, total carbon emission and total waste output. These indicators can be used as an important basis to evaluate the cost control effect of green supply chain.

In the deep reinforcement learning method, the purpose of green supply chain modeling is to quantify and mathematize the environmental and economic factors of the supply chain to provide input and optimization target for subsequent reinforcement learning algorithm. By establishing an appropriate mathematical model, the cost control problem in supply chain can be better understood, providing guidance for the design and optimization of reinforcement learning algorithm (Das et al., 2023)(Yi et al., 2023).

3.2 Application of reinforcement learning in green supply chain

By applying reinforcement learning to green supply chain management, intelligent decision-making and optimization can be realized, and environmental performance and economic benefit of supply chain can be improved. Firstly, reinforcement learning can be applied to decision-making in the green supply chain. By establishing appropriate state space and action space, the intelligent agent can choose the optimal decision action according to the current environmental state, so as to reduce carbon emission, waste generation and other green indicators (Sun & Guo, 2023). For example, intelligent agent can make key decisions on amount purchased, production plan and logistics path and so on based on the real-time data and environmental requirements of supply chain, thus achieving the greening and optimization of supply chain. Secondly, reinforcement learning can be used for resource management and scheduling optimization in green supply chain (Lihour et al., 2023). In the supply chain, the rational utilization of resources is very important for green cost control. Through reinforcement learning algorithm, resource allocation and scheduling strategies can be learned and optimized to maximize resource utilization efficiency and reduce environmental cost. For example, intelligent agent can learn how to adjust production line capacity allocation under different supply and demand situations to avoid excess or shortage of resources and achieve balance and optimization of green supply chain (Yang, 2023). In addition, reinforcement learning can be applied to risk management and forecasting in green supply chain. Green supply chain is facing various risks from environmental change, market fluctuation and so on. Through reinforcement learning algorithm, risks can be modeled and predicted, and corresponding measures can be taken for risk management. For example, intelligent agent can reduce uncertainties and risks in the supply chain and improve the robustness and sustainability of the supply chain by learning and optimizing decision-making strategies (Shi, 2023).

3.3 Optimizing cost control strategy with deep learning and reinforcement learning

By combining deep learning and reinforcement learning method, more precise, intelligent and dynamic cost control strategies can be achieved to improve the green performance and economic benefit of supply chain. Firstly, deep reinforcement learning can be applied to the modeling and optimization of cost control strategy. By using deep neural network, plenty of supply chain data can be processed and complex cost control strategies can be learned. Deep neural network can model the state of supply chain, including supplier selection, logistics route selection, production planning, etc., and predict its impact on cost and green indicators (Liu C. et al., 2023). By combining with reinforcement learning algorithms, intelligent agent can learn optimal decision strategies to maximize economic benefits and minimize environmental cost. Secondly, deep reinforcement learning can optimize cost control through simulated environment and real-time decision making. By building a virtual supply chain environment, various cost control strategies can be simulated and evaluated to find the optimal decision-making strategy. Intelligent agent can learn and optimize its own decision-making strategy by interacting with the virtual environment to cope with uncertainties and changes in the actual supply chain (Yue et al., 2023). At the same time, deep reinforcement learning can also realize real-time decision-making and adjust cost control strategies dynamically according to real-time data and environmental requirements of supply chain, so as to achieve more accurate and flexible green supply chain management. In addition, deep reinforcement learning can be combined with other optimization techniques, such as evolutionary algorithm and genetic algorithm, to improve the effectiveness of cost control strategies further. By combining different optimization methods, their advantages can be used fully to optimize the cost control of green supply chain from multiple angles and levels. This combination method can find better solutions in the complex supply chain environment and improve the green performance and economic benefits of the supply chain (He et al., 2023).

4. Application of deep reinforcement learning in building green and low-carbon cities

4.1 The application of deep reinforcement learning in the field of urban transportation

Through combining the methods of deep learning and reinforcement learning, intelligent traffic management and optimization can be achieved to improve traffic efficiency, reduce energy consumption and carbon emission. On the one hand, deep reinforcement learning can be applied to the optimization of traffic signal control. Traditional traffic signal control methods often rely on fixed plan or static schedule and cannot flexibly cope with real-time traffic flow changes. However, deep reinforcement learning can learn the optimal signal control strategy through real-time interaction with the traffic environment. Intelligent agent can sense the traffic flow, road conditions and other information, and select the optimal signal light timing according to the current state to maximize traffic fluency and energy utilization efficiency (Wang et al., 2022). Through the optimization of deep reinforcement learning, traffic congestion can be reduced and travel time can be shortened, thus reducing traffic emission and energy consumption. On the other hand, deep reinforcement learning can be applied to traffic path planning and navigation system optimization. The traditional route planning method is usually based on static map information and fixed road condition prediction, which cannot adapt to the real-time traffic state and the change of individual travel demand. However, deep reinforcement learning can provide users with personalized optimal route and navigation suggestions by learning and optimizing route selection strategies, based on real-time traffic data and users' travel preference. Intelligent agent can constantly optimize route planning strategies through interaction and feedback with users to provide more accurate and efficient navigation service. The application of deep reinforcement learning can reduce traffic congestion and driving distance, thus reduce energy consumption and carbon emission. In addition, deep reinforcement learning can also be applied to traffic pattern recognition and prediction. Deep learning technology can process a large amount of traffic data, such as sensor data and video data, from which traffic patterns and rules can be extracted (Ren, 2022). The intelligent agent can learn and predict the traffic flow and congestion, and provide accurate traffic prediction information for traffic managers and travelers, so they can make corresponding adjustment and decision. Through the application of deep reinforcement learning, traffic conditions can be predicted in advance, to optimize transportation resource allocation and reduce unnecessary energy consumption and environmental impact. In conclusion, the application of deep reinforcement learning in the field of urban transportation can realize intelligent traffic management and optimization, improve traffic efficiency and reduce energy consumption and carbon emission. Through the learning and optimization of intelligent agent, intelligent decision-making and personalized service in traffic signal control, route planning and navigation system can be realized, providing important support and driving force for the construction of green and low-carbon cities. The application of deep reinforcement learning will further enhance the sustainability of urban transportation system and bring great potential for the development of smart cities in the future (Wang, 2022).

4.2 The application of deep reinforcement learning in energy management

Energy management is one of the important fields in building green and low-carbon cities, and the application of deep reinforcement learning in energy management has great potential. By combining deep learning and reinforcement learning, intelligent energy production, distribution and consumption can be optimized to improve energy efficiency and reduce carbon emission and environmental impact. Deep reinforcement learning can be applied to the optimization of energy production and supply. By learning and simulating the operation of energy production system, the intelligent agent can automatically adjust the strategy and parameters of energy production to maximize the efficiency of energy production and the utilization of renewable energy. Through the perception of real-time energy data and environmental needs, intelligent agent can optimize energy supply planning and scheduling to reduce energy waste and loss (Zhang & Dong, 2022). At the same time, the intelligent agent can also optimize the energy procurement strategy according to the changes of energy market and demand forecast, and realize the intelligent energy procurement and supply chain management to ensure the reliable supply and green utilization of energy. In addition, deep reinforcement learning can be applied to optimize energy consumption and use. By combining the methods of deep learning and reinforcement learning, personalized energy management recommendations and optimization strategies can be provided to individual users and energy consumers. By learning users' energy consumption patterns, behavioral preference and environmental conditions, the intelligent agent can make optimal energy use plans and adjustment suggestions for users. Through real-time monitoring of energy consumption data and users' feedback, intelligent agent can continuously optimize energy consumption strategies and guide users to achieve energy conservation, emission reduction and green lifestyle. In addition, deep reinforcement learning can be combined with smart home technology to realize intelligent control and optimization of energy equipment, improve energy utilization efficiency and users' comfort level (Yang & Xu, 2021). In addition to energy production and consumption optimization, deep reinforcement learning can also be applied to the planning and design of energy systems. By learning and optimizing the structure and parameters of the energy system, intelligent agent can propose the optimal energy system planning scheme, including the selection of energy source, the layout of energy facilities and the optimization of energy network. By combining with energy system simulation and optimization tools, deep reinforcement learning can provide energy planners and decision makers with more accurate and efficient energy system design and decision support, and achieve an intelligent and green energy system. In conclusion, the application of deep reinforcement learning in energy management can realize intelligent optimization of energy production, distribution and consumption. Through the learning and optimization of intelligent agent, intelligent regulation of energy production and supply can be realized, energy consumption and using strategy can be optimized, as well as intelligent planning and design of the energy systems can be realized. The application of deep reinforcement learning will further promote innovation and sustainable development in the energy sector and provide important support and impetus for the construction of green and low-carbon cities (Fan, 2021).

4.3 The application of deep reinforcement learning in waste management

Waste management is an important part in building green and low-carbon cities, and the application of deep reinforcement learning in waste management can provide intelligent waste treatment and resource recovery schemes to promote waste reduction, resource recycling and environmental protection. Deep reinforcement learning can be applied to the optimization of waste sorting and recycling. Waste classification is the key step to realize effective utilization of waste resources, but the traditional waste classification methods often need a lot of manpower and time cost, and there is a problem of inaccurate classification. Deep reinforcement learning can realize automatic waste classification system by learning the image features and classification rules of waste. The intelligent agent can sense and recognize the characteristics of waste, automatically judge the category of waste according to the existing waste classification knowledge and rules, and correctly allocate it to the corresponding recycling process. Through the application of deep reinforcement learning, the accuracy and efficiency of waste classification can be improved, the recycling of resources can be promoted and the impact of waste on the environment can be reduced (Wang, 2020). In addition, deep reinforcement learning can be applied to the optimization of waste disposal processes. Waste treatment involves the collection, transportation, treatment and disposal of waste, and deep reinforcement learning can realize intelligent and efficient waste treatment process by learning and optimizing waste treatment strategy and method. The agent can sense the waste treatment environment and real-time data, and select the optimal waste treatment scheme and operation strategy according to environmental requirements and resource constraints. By interacting with waste treatment equipment and system, the intelligent agent can automatically adjust and optimize the parameters and operation of waste treatment to achieve the best treatment effect and resource utilization efficiency. The application of deep reinforcement learning can improve the efficiency and environmental protection of waste treatment and reduce the cost and environmental risks. Deep reinforcement learning can also be applied to support and optimize waste management decisions. Waste management involves all aspects of waste generation, collection, treatment and disposal, etc. Deep reinforcement learning can provide decision support and optimization suggestion by learning and optimizing decision-making strategy of waste management. Agents can analyze the complex relationship and interaction effect of waste management, predict the effect and risk of waste management, and generate the optimal waste management decision scheme according to different objectives and constraints. By interacting with waste management decision makers, intelligent agent can provide personalized decision-making suggestions and optimization schemes, which can help decision makers to formulate waste management policies and measures better to achieve intelligent and sustainable development of waste management (Hu et al.,2017) (Li & Chu, 2017). In conclusion, the application of deep reinforcement learning in waste management can provide intelligent waste treatment and resource recovery schemes, promote waste reduction, resource recycling and environmental protection. Through the learning and optimization of the intelligent agent, the intelligent waste classification and recycling can be realized, the waste treatment process can be optimized, and the support and optimization of waste management decision-making can be provided. The application of deep reinforcement learning will provide important technical support and impetus for the construction of green and low-carbon cities and sustainable development (Li, 2014).

5. Conclusion

In the process of building green and low-carbon cities, deep reinforcement learning, as a cutting-edge technology, has wide application potential and important role. This paper discusses the application of deep reinforcement learning in green supply chain and waste management for green supply chain cost control and green low-carbon city construction (Zhou, 2011).

In terms of the cost control of green supply chain, deep reinforcement learning can improve the efficiency and sustainability of supply chain and reduce carbon emission and environmental impact by modeling green supply chain and optimizing cost control strategy (Gee & Won-Il, 2023). In terms of building green and low-carbon cities, the application of deep reinforcement learning plays an important role in urban transportation, energy management and waste management. It can realize intelligent traffic management and optimization, improve traffic efficiency and reduce energy consumption; In terms of energy management, deep reinforcement learning can optimize energy production and consumption strategy, improve energy utilization efficiency and reduce carbon emission (Abin, 2023). In terms of waste management, deep reinforcement learning can realize intelligent waste classification and recycling, optimize the waste treatment process, and promote waste reduction and resource recycling.

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