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The Dynamic Regulation Mechanism and Optimization of the Carbon Emission Rights Market in the Era of Low-Carbon Economy

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SUMMARY: *Under the background of low-carbon economic development, carbon emission trading, as an important institutional arrangement, can effectively coordinate the role of emission reduction constraints, price signals and resource allocation. However, there are still some problems in the current market operation, such as wide and large amount of emission data, wide range of price transmission and long chain, and lagging regulation. In this paper, how to realize the dynamic regulation of carbon emission trading in carbon emission market is studied. With the help of computer science, an intelligent computing support system based on data layer, modeling layer, decision layer and interaction layer is constructed. Based on the system, the carbon emission monitoring and prediction model, the carbon quota market price change prediction model, and the dynamic adjustment optimization model of carbon emission trading using deep reinforcement learning method were established. Finally, the closed-loop system of "monitoring-prediction-decision-feedback" is obtained. Finally, the system is simulated and the effectiveness of different control strategies is compared. The results show that the proposed DRL strategy outperforms the benchmark strategy and MILP strategy in terms of net income, volatility control, and response efficiency. In the typical 30-day simulation window, the cumulative net income reaches 7.52 million yuan, the carbon price volatility rate drops to 8.7%, the compliance deviation rate drops to 3.2%, and the average adjustment response duration is shortened to 6 minutes. The study suggests that embedding intelligent computing in the adjustment process of the carbon emission rights market helps improve the accuracy, forward-looking nature, and coordination of market operation.*
Povzetek: Študija obravnava uporabo tehnologije navidezne resničnosti pri športnem pouku. Združuje računalniški vid, 3D rekonstrukcijo skeleta, semantično prepoznavanje gibov in virtualno interakcijo. Rezultati kažejo boljšo vizualizacijo gibov, hitrejšo povratno informacijo in večjo interaktivnost. Kljub temu ostajajo izzivi pri večuporabniških scenarijih, udobju opreme, stabilnosti sistema in stroških uvajanja v šolski učni praksi.

KEYWORDS: *Low-carbon economy; Carbon emission rights market; Dynamic adjustment; Deep reinforcement learning*

1 Introduction

As the low-carbon economy continues to advance, carbon emission reduction is no longer merely an environmental governance issue; instead, it has deeply integrated into the energy structure adjustment, industrial transformation and upgrading, and regional competitive landscape reshaping. The carbon emission market based on total emission control and

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supported by trading means can organically link emission constraints, price signals and enterprise behavior, and alleviate the problems of improper allocation of resources and fixed emission reduction costs under government regulation alone to a certain extent. And through the form of quota allocation, market transaction and payment for performance, the system with both environmental attributes and economic incentive characteristics has gradually formed. Thus, it has become an important support system for low-carbon economic development.

However, there are still two factors that affect the smooth operation of the carbon market. First, the basic data of the carbon market has obvious inunity and dynamic change characteristics. Second, the data sources and timeliness of enterprise emission monitoring data, industry production capacity, energy consumption level and trading behavior are different, and their accuracy and standardization will directly affect the quota calculation, price formation and risk management results. Third, the market operating environment has the characteristics of high dimension and non-static. Factors such as electricity price changes, economic development situation, the possibility of policy mutation and the game behavior of participants interact with each other, resulting in drastic fluctuations in carbon price. In such a multidimensional changing environment, it is difficult to achieve timely and effective response accuracy by traditional adjustment methods that simply use historical experience, rules or a single quantitative model.

Solving the above problems, especially the problem of carbon emission market regulation, is inseparable from the development and application of computer technology, and requires the help of big data analysis, artificial intelligence, machine learning and other new technologies and methods to provide new ideas and technical means. In recent years, related research has gradually focused on carbon price prediction, market efficiency assessment, and policy effect identification, but existing results are mostly concentrated on analysis of individual links, and there is still a lack of a dynamic adjustment system that can integrate "monitoring - prediction - decision - feedback" throughout the process. Especially in market adjustment practices, how to combine multi-source carbon data perception, price fluctuation prediction, adjustment strategy generation, and interpretable human-machine collaborative decision-making is still a major problem restricting the refined operation of the carbon market. Based on this, this paper focuses on the dynamic adjustment mechanism and optimization of the carbon emission rights market in the low-carbon economy era, combining computer modeling and intelligent optimization methods, to construct a dynamic adjustment system framework and explore key technical models and their application paths, with the aim of providing references for improving the efficiency, stability, and regulatory accuracy of the carbon market.

1.1 Review of Related Research

Research on the operation and optimization of the carbon emission rights market in China and abroad has generally followed two paths. One type of research focuses on system design, price formation mechanisms, and their influencing factors, mainly examining the basic logic of quota market operation, including quota allocation rules, compliance constraints, energy price fluctuations, macroeconomic prosperity, and policy expectation changes [1]; Christiansen et al., Hintermann et al., Bredin et al., and Chevallier et al. explained the formation and fluctuation mechanism of the EU ETS price from the perspectives of energy prices, economic cycles, and market expectations [2-5]; Creti et al., Aatola et al., Koch et al., and Fan et al. further revealed the differentiated effects of energy structure, policy revisions, and external economic shocks on carbon price evolution in different trading stages [6-9]. These studies provided important evidence for understanding the sources of carbon market fluctuations and the constraints of the system, but overall they were more focused on post-event explanations and phased tests, and still lacked support for real-time operation dynamic adjustment.

The second type of research has begun to involve the analysis of market effectiveness, government behavior, or mathematical models. Borghesi et al. started from the market stability reserve mechanism and discussed the boundaries of the impact of institutional tools on market stability [10]; Weng et al., Long et al., and Wu et al. evaluated the construction logic, operational performance, and emission reduction effect of the Chinese carbon market, indicating that the market mechanism has played a role in institutionalizing resource allocation and emission reduction incentives, but also exposing practical problems such as insufficient market depth, limited price elasticity, and slow adjustment response [11-13]. On this basis, Tang et al., Zhao et al., and Gao et al. respectively advanced the research on carbon market regulation from aspects such as dynamic general equilibrium, market efficiency evaluation, and policy implementation effect [14-17]. With the development of computer technology, some scholars began to apply computational intelligence, different frequency economic and energy data, and neural network hybrid models to carbon price prediction, promoting the research to shift from static explanations to data-driven identification [18-20]. However, the existing results are mostly concentrated on single tasks, such as price prediction, efficiency measurement, or policy effect identification, and the attention to the closed-loop regulation system that integrates emission monitoring, price prediction, strategy optimization, and feedback correction is still insufficient. As shown in Table 1, the existing research still has significant differences in method systems, real-time capabilities, and system integration levels. Based on this, this paper attempts to establish a linkage relationship between carbon emission data perception, carbon price fluctuation prediction, and deep reinforcement learning optimization, and construct a dynamic regulation mechanism for the carbon emission rights market in the era of low-carbon economy.

Table 1: Comparative Analysis of Research on Carbon Emission Rights Market

Research Category	Representative References	Research Focus	Main Methods	Support for Dynamic Regulation	Limitations
Institutional Design and Price Mechanism Studies	[1]-[10]	Market design, price formation, policy shocks, stability mechanisms	Theoretical analysis, econometric regression, policy evaluation	Can explain sources of market fluctuations and provide institutional basis for regulation	Emphasizes ex-post explanation; weak real-time response capability
Operation and Performance Studies of China's Carbon Market	[11]-[17]	Market development paths, operational efficiency, emission reduction effectiveness, policy adaptation	Literature review, empirical testing, efficiency evaluation, CGE models	Identifies institutional characteristics and practical issues in China's carbon market	Insufficient discussion of dynamic regulation processes and online optimization
Carbon Price Prediction and Intelligent Computing Studies	[18]-[20]	Carbon price volatility prediction, multi-source data utilization, nonlinear modeling	Computational intelligence, hybrid models, neural networks	Provides predictive support for market early warning and regulation decisions	Focuses on single prediction tasks; lacks integrated closed-loop system
This Study	[1]-[20]	Dynamic regulation mechanisms and optimization pathways	Joint modeling of emission monitoring, price forecasting, and deep reinforcement learning	Constructs a "monitoring—prediction—decision— feedback" closed-loop regulation framework	Requires further validation across more market scenarios

1.2 Research Questions and Innovative Contributions

Based on the aforementioned research progress and practical needs, this paper intends to construct a dynamic regulation framework for carbon emission rights market driven by intelligent computing, and incorporate emission monitoring, price prediction, strategy optimization, and feedback correction into a unified system for examination. The focus of this article is not only on the prediction accuracy of a certain local model, but also on whether the market regulation process can form a coordinated mechanism of continuous response, stable operation, and interpretable decision-making. With this goal in mind, this paper attempts to answer the following questions: In the context of a low-carbon economy, in a carbon market environment with high volatility and strong correlation, can a data-driven dynamic regulation system more effectively improve market operation efficiency and quota allocation quality compared to traditional static regulatory methods; how can multi-source emission data, transaction data, and energy economic data achieve coordinated perception and linkage analysis within a unified computing framework; what kind of connection should be established among carbon emission quantity prediction, carbon quota price fluctuation prediction, and dynamic optimization decision-making to enhance the timeliness and adaptability of the regulation strategy; after introducing intelligent optimization methods such as deep reinforcement learning, how can we avoid model decisions remaining at the "black box" level and enhance the interpretability and application credibility of market regulation.

Regarding these questions, the main contributions of this paper are as follows: In terms of research content, it advances the discussion of carbon emission rights market regulation from a single price analysis or policy evaluation to an overall discussion of the "monitoring—prediction—decision—feedback" closed-loop mechanism; in terms of method design, it combines computer technology to build emission monitoring and prediction models, price fluctuation prediction models, and dynamic regulation optimization models based on deep reinforcement learning, enhancing the system's ability to identify and respond to complex market disturbances; in terms of application, it proposes a system architecture and technical implementation ideas for carbon market operation, forming a continuous relationship between data collection, model training, strategy output, and result evaluation; in terms of research value, it attempts to combine intelligent optimization models with market regulation practice, providing a more operational analytical framework for the refined governance of the carbon emission rights market in the low-carbon economy era.

The framework of this paper is as follows: Section 2 describes the carbon emission trading market under the background of low carbon economy; Section 3 is the overall design of the dynamic adjustment system based on the background. Section 4 is the core algorithm and optimization model construction. Section 5 conducts the system implementation and gives the case analysis. Finally, we discuss the results in more detail in Chapter 6. In the final chapter, Chapter 7, we will summarize our arguments and give an outlook.

2 Overview of the Operation of the Carbon Emission Rights Market in the Context of Low-Carbon Economy

2.1 The Connotation and Composition of the Carbon Emission Rights Market

Carbon emission trading market is a special commodity market based on a certain amount control and trading with emission quota as the main subject matter. Its essence is to use market-based means to allocate emission quota. The carbon emission constraint is transformed into quantifiable, tradable and supervised market rules, so that each subject can take the way of trading to achieve the lowest cost reduction combination in the same performance process. As shown in Figure 1, it involves the process of quota management, emission monitoring, trading docking, deposit payment and regulatory feedback, and the operation mechanism of "government and enterprise supervision and municipal report and determination" is formed.

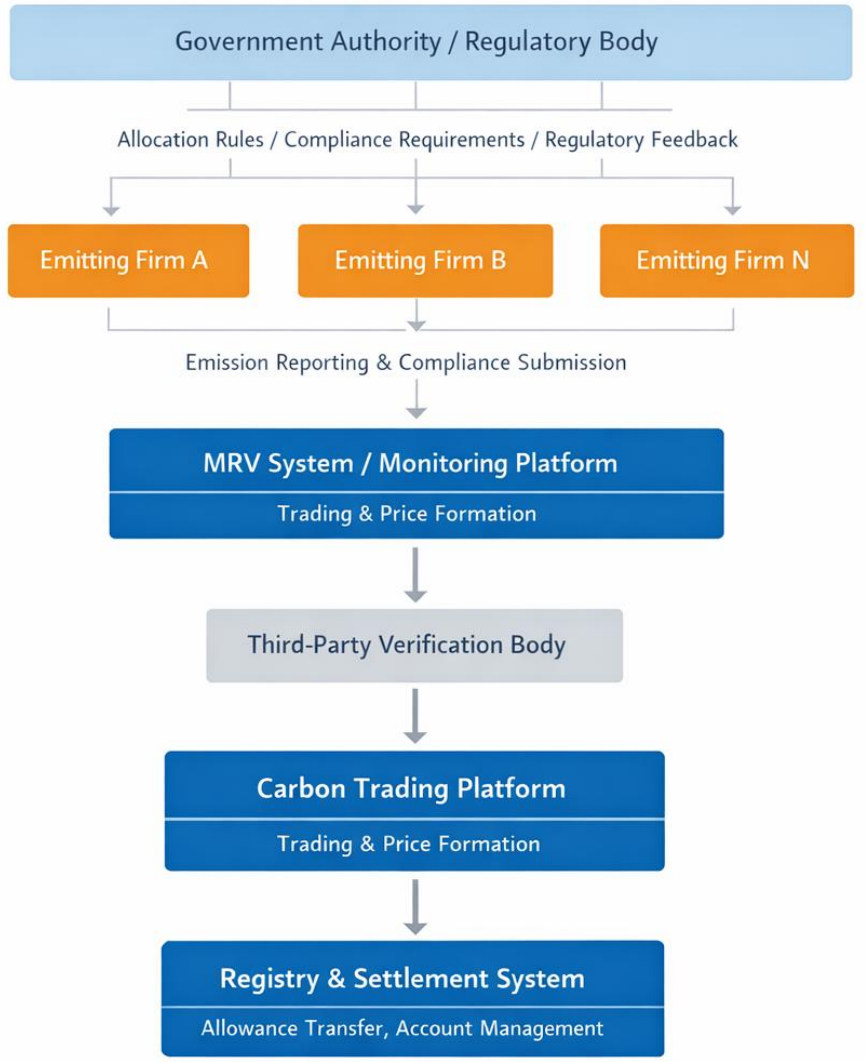

Figure 1: Schematic Diagram of the Basic Composition of the Carbon Emission Rights Market

In the framework, the main participants in the carbon market include quota allocation agencies, key emission enterprises, verification agencies, exchanges, registration systems, and regulatory authorities. Among them, the key emission enterprises are the main subjects of quota holding and trading. The exchange undertakes the functions of making deals and information disclosure; The registration system is responsible for account management and quota transfer; The audit department and supervision department are responsible for ensuring the authenticity of emission data and the standardization of the market. Under the supervision of information technology, carbon emission monitoring platform, data interface, intelligent computing module has become a part of the market infrastructure.

2.2 The Core Role of Carbon Emission Data in Market Regulation

In the operating carbon market, carbon emission data is one of the important basic facilities, which plays an important role in quota allocation, price discovery and compliance verification. Specifically, it is reflected in the following aspects: First, it is the basic basis for quota verification. The actual emission of an enterprise relates to the determination of the surplus and deficit of the enterprise's quota, and then decides whether to buy or sell and the pressure of performance. The third is the source of change. Changes in emission intensity, capacity utilization rate and energy consumption structure of key industries will be transmitted to carbon price through expected trading, and then act on market supply and demand relationship. The fourth is the source of regulation. Only stable and traceable data flow can help managers detect anomalies in time and adjust quota allocation, performance progress and early warning accordingly. The general formula of carbon emissions is as follows.

$$E = \sum_{i=1}^{n} A_i \times EF_i \times O_i \tag{1}$$

where: E represents the total carbon emissions in the accounting period; A_i is the level of type i energy activity; EF_i is the corresponding emission factor; O_i is the oxidation rate or correction factor. The formula provides a simple accounting basis for tracking and measuring carbon emissions, and can be used as a basis for market regulation. Digital collection of instantaneous data into the warehouse, supplemented by intelligent processing and analysis system, can improve the timeliness and reliability of sewage discharge, and enhance the ability of transaction regulation.

2.3 Carbon Emission Rights Market Trading and Regulation Mechanism

The operation process of carbon emission permit market based on overall constraints includes quota allocation, secondary market trading, contract performance and tax payment. Quota allocation determines the initial supply, and enterprises buy or sell in the market according to their own emissions and quota holdings. The secondary market transaction converts the economic cost of greenhouse gas emission reduction into a tradable market signal by bidding and matching the buyer to form a carbon price. Quotas for performance can only be reset after verification, making them more binding. Trading volume, price volatility, compliance and emissions changes are all taken into account by government departments. Thus, the quota distribution rhythm, early warning threshold and stability mechanism coefficient can be adjusted in time. At the same time, the application of computer technology makes the transaction monitoring, anomaly identification, strategy simulation and other work from manual analysis to data analysis, and realizes the timely and fine management of carbon market.

2.4 Realistic Challenges Faced by Dynamic Regulation of the Carbon Emission Rights Market

The dynamic management of carbon trading market is mainly a dynamic adjustment process of quota supply, trading rate, risk early warning and other parameters for the purpose of total volume control, price stability and fair performance. It is not a single linear relationship, but a dynamic balance process determined by the authenticity of emission data, the fluctuation of electricity price and the willingness of enterprises to trade. As can be seen from Table 2, the main problems of the current dynamic pricing mechanism of carbon emission permits market are as follows: 1) the basic data are not reliable; 2) the conduction chain is too long; 3) Response lag; 4) Insufficient intelligent assistance. If the above problems cannot be solved, it may cause problems such as moving from real to virtual, short-term performance pressure accumulation, and asymmetric effect of price adjustment measures. Therefore, the construction of a computer-based real-time monitoring, forecasting and optimization decision-making platform has become an essential part of improving the control level of the carbon quota market.

Table 2: Main Challenges Faced by the Dynamic Regulation of the Carbon Emission Rights Market

Challenge Category	Specific Manifestation	Impact on Market Regulation
Data Foundation Issues	Emission data are dispersed in sources, updated at different frequencies, and verification cycles are long	Difficult to promptly identify real supply-demand changes
Price Volatility Issues	Energy prices, policy expectations, and trading sentiment interact and propagate	Easily amplifies short-term market fluctuations
Regulation Timeliness Issues	Quota adjustments and early-warning interventions are mostly implemented in stages	Regulatory measures lag behind market changes
Technical Support Issues	Insufficient capabilities for online prediction, anomaly detection, and strategy optimization	Hard to form a closed-loop dynamic regulation system

3 Intelligent Computing-driven Dynamic Regulation System for Carbon Emission Rights Market

3.1 System Design Concept

Aiming at the problems of data dispersion, large price fluctuations and slow response speed in the carbon trading market, a dynamic adjustment mechanism based on intelligent computing technology was proposed, and the construction was carried out according to the following four principles: first, data-driven as the core, pollution monitoring data, trading data, energy price information and policy information were unified under the framework of data analysis model. Strengthen the speed of market identification; The second aspect is based on model engine, using prediction mode and improvement mode to work together to improve the accuracy and pertinence of debugging strategy generation. The third aspect is to emphasize man-machine collaboration, combining the real-time analysis function of the computer system and the decision-making ability of the manager's rules and regulations, and avoiding the problem that the debugging process depends too much on experience or completely on the model. The fourth is to highlight the evolutionary characteristics and realize the system to constantly revise the parameters and strategies according to the market feedback, so as to cope with the changing needs of the carbon market operation environment under the low carbon economy.

3.2 Overall Architecture and Dynamic Adjustment Process

Aiming at the problems of wide monitoring range, complex transmission of price fluctuations and slow regulation response in carbon trading market, this paper proposes a rapid regulation mechanism based on intelligent computing. Based on the three basic ideas of information exchange, model mutual promotion and strategy mutual feedback, a complete regulation mechanism framework including market perception, trend prediction, strategy generation and effect feedback is established. As shown in Figure 2, the system is a bottom-up hierarchical modular architecture, which can be divided into four levels: data module, algorithm module, execution module and interactive feedback module. The design principle is that each subsystem is relatively independent and cooperates with each other, and the scalability and stability of the whole system are guaranteed.

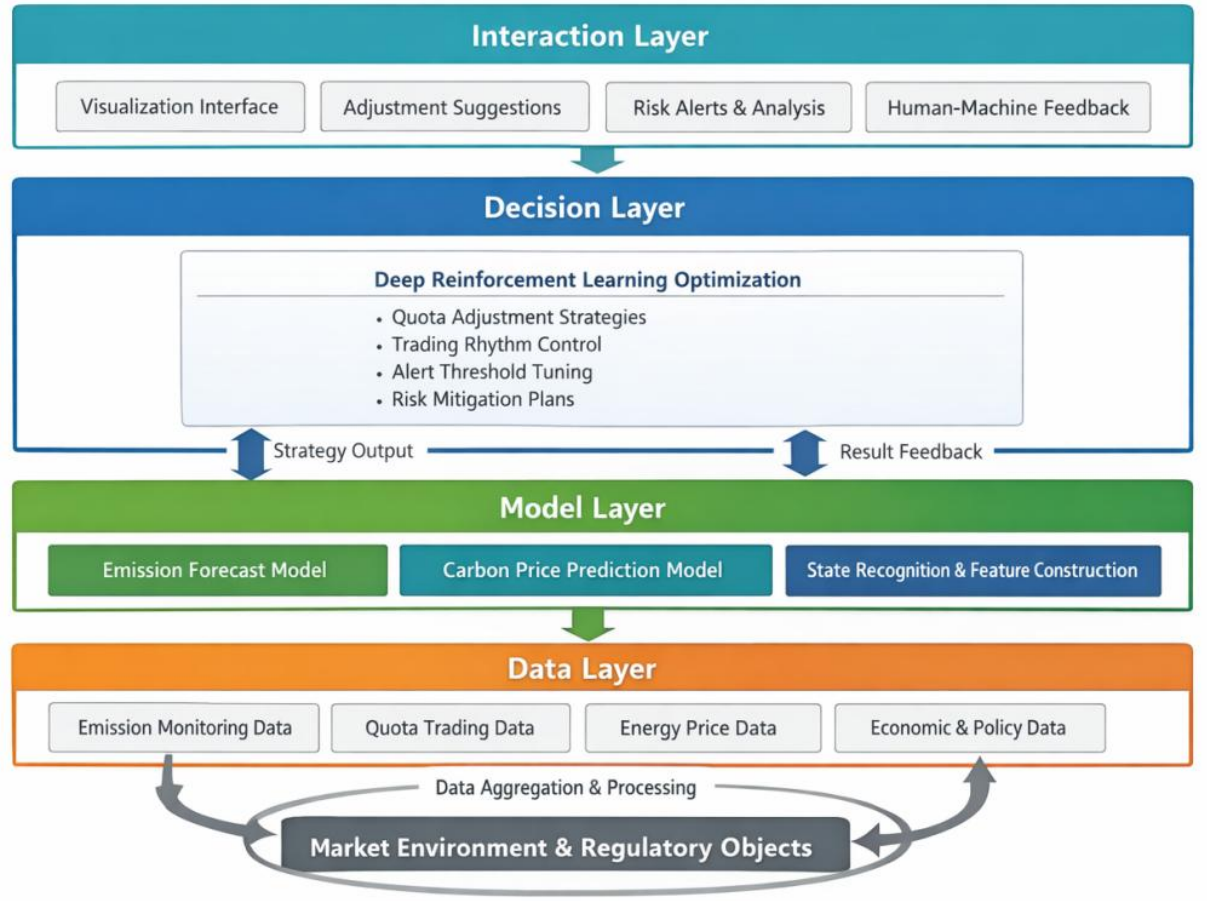

Figure 2: Overall architecture and process of the dynamic regulation system for carbon emission rights market driven by intelligent computing

The system consists of two interrelated data streams. The first one is the master data flow from the data end, which collects enterprise carbon emission monitoring data, quota ownership and trading data, energy price data, macroeconomic data and policy information changes, and applies database, real-time transmission technology and interface technology to preprocess all data. After cleaning, alignment and attribute extraction, the above information is transferred to the carbon emission prediction unit and the carbon quota price change prediction unit to form the fusion attribute vector characterizing the current market state, and is transferred to the decision-making link for subsequent dynamic adjustment reference. The other core element is the policy update iterative algorithm flow. This is the key link to realize the dynamic adjustment of the system. When the regulator obtains the information of the market state, it calls the deep reinforcement learning optimizer to generate a set of strategies, including quota adjustment suggestions, warning line adjustment, trading rate control, risk management, etc. Then the strategy is executed and the market feedback information such as market price change, trading activity, performance pressure, and emission gap is received. On the one hand, the feedback information is transmitted to the result evaluation module to judge whether the current round of correction is effective; on the other hand, it will return to the model module and decision-making stage to trigger the parameter correction action and the strategy repeated execution mechanism, and the closed-loop operation process of "state perception - strategy formulation - market response - model correction" is formed.

On this basis, the dialogue layer connects the simulator with the regulator: the regulator sees the market, sees the strategy suggestions, and how these strategies work. The system converts the results of the model into simple parameter adjustment signals and risk information. Therefore, intelligent computing is not only a back-end server, but also a live cooperation mechanism formed by the regulation stage of the market and the decision of the regulator. To sum up, we can integrate the multi-source information collection and regulation strategy update, which provides us with technical means for fine and real-time management of carbon emission trading market.

3.3 Analysis of the Mechanism of Each Functional Layer

The functional modules of each level do not exist in isolation. In the process of continuous information interaction and decision-making response, they support the dynamic management mechanism of carbon market. The bottom layer is the data layer, which is used to obtain enterprise pollutant monitoring information, carbon quota trading information, electricity price information, economic operation indicators, policies and regulations related information, and carry out cleaning, verification, comparison and storage. This level not only has the function of data acceptance, but also is an important part of market situation identification. The consistency and availability of multi-source heterogeneous data are improved by using database management methods, interface extraction methods, and outlier elimination methods, so as to ensure stable input for subsequent model operations.

The most important one is the model layer at the bottom, which mainly includes emission monitoring and forecasting model, carbon quota price trend forecasting model and state attribute generation module. At this level, it is not only necessary to identify the emission characteristics of enterprises, the change of market supply and demand and the trend of price fluctuation, but also can use scattered information to form a state vector for reference decision-making, and finally complete the process of transforming basic data into market state with control significance. Each model does not exist independently from each other, but is called, refrezed and fed back every certain period, which ensures that the forecast results can adapt to the market changes in real time.

The decision layer is the key link of making policy, which is a dynamic process. Based on the market state information feedback from the model layer, the deep reinforcement learning method is used to optimize the processing, and the optimal quota control intensity, early warning threshold, transaction rate and risk control path are obtained, and the optimal regulation scheme is obtained under the above multiple constraints. When these strategies are put into the market, the newly generated price level, trading volume, performance load and emission margin will be transmitted back to the system to further adjust the strategy parameters.

The interactive feedback layer provides visual display and human-computer interaction functions. At this level, the complex model output can be transformed into trend charts, early warning tips and optimization schemes for the regulatory authorities to make decisions and responses on the basis of grasping the strategy rules. In this way, the closed-loop linkage mechanism of data perception, model analysis, strategy generation, and feedback correction is formed, and the system transforms from a static analysis tool to a dynamic adjustment platform for market operation.

4 Key Technologies and Optimization Model Construction

4.1 Carbon Emission Monitoring and Prediction Model

In the key module of the dynamic adjustment system, the monitoring and prediction of carbon emissions is the prerequisite for subsequent price analysis and strategy generation. If the emission data collection is inaccurate or the trend judgment is significantly deviated, the supply and demand relationship of carbon quotas cannot be accurately identified, and the adjustment mechanism will lose a reliable anchor. Therefore, in the model construction, this paper follows the concept of "accounting for traceability, monitoring for accessibility, and prediction for iteration", combining the enterprise emission accounting logic with the intelligent time-series prediction method to form a carbon emission monitoring and prediction model oriented towards market operation.

In the monitoring stage, the model is based on enterprise energy activity data, production data, equipment operation parameters, and online monitoring data to conduct itemized accounting for key emission sources. Considering the differences in calorific value, carbon content coefficient, and oxidation level among different energy types, the carbon emission of the enterprise at time t can be expressed as:

$$C_{i,t} = \sum_{r=1}^{R} \left(EC_{i,r,t} \times NCV_r \times CF_r \times OX_r \right) - S_{i,t} \tag{2}$$

In this formula, $C_{i,t}$ represents the carbon emission volume of the i-th enterprise at time t; $EC_{i,r,t}$ represents the consumption volume of the r-th type of energy; NCV_r represents the average low calorific value of this energy; CF_r represents the carbon coefficient per unit of heat value; OX_r represents the oxidation rate; $S_{i,t}$ represents the carbon quantity that can be reduced or recycled. This formula can convert scattered energy consumption information into comparable emission results, providing a unified standard for identifying the emission status at the enterprise level and the market level.

In the prediction stage, relying solely on the static kernel algorithm is difficult to cope with the temporal fluctuations in carbon emissions caused by changes in production load, energy structure, and policy constraints. Based on this, this paper introduces a long short-term memory network with attention mechanism to conduct dynamic learning of multi-source feature sequences. Its prediction process can be written as:

$$\hat{C}_{t+1} = W \left(\sum_{\tau=t-p+1}^{t} \alpha_\tau h_\tau \right) + b, h_\tau = LSTM(x_\tau, h_{\tau-1}) \tag{3}$$

In this model, $\hat{C}_{t+1}$ represents the predicted carbon emission quantity for the next time period; x_τ is the input feature vector, which includes variables such as energy consumption intensity, capacity utilization rate, process load, historical emissions, and meteorological conditions; h_τ is the hidden state; α_τ is the attention weight, used to depict the contribution of different historical time points to the current prediction; W and b are the parameters of the output layer. This model can simultaneously capture the short-term fluctuations and phased changes of the emission sequence, enabling a more comprehensive expression of high-energy-consuming process switching, seasonal load variations, and abnormal emission disturbances.

In short, the model realizes the integration process of "real-time monitoring, emission measurement and prediction". On the one hand, its existence ensures the observability of emissions and avoids the prediction deviation of carbon accounting basis. On the other hand, the recognition ability of complex disturbances is enhanced based on computer simulation, which is helpful to provide a relatively stable scenario input for predicting and optimizing the future carbon price.

4.2 Prediction Model for Carbon Quota Price Fluctuations

The carbon quota price is affected by factors such as supply and demand balance, energy prices, performance time, policy expectations and market sentiment, and is highly unstable, phased and nonlinear. Only using the traditional time series model to study the data is difficult to fully mine the association relationship between each time node, and it is also difficult to describe the impact of unexpected policy information on short-term prices. Therefore, the attention mechanism Transformer model is used to construct the prediction model of carbon quota price change, and the historical carbon price, trading volume, coal price, gas price, industry emission intensity and performance time node are incorporated into the input sequence. And took a self - care approach to timely make the necessary corrections. The main algorithm flow can be expressed as follows.

$$\mathrm{Attention}(\mathrm{Q},\mathrm{K},\mathrm{V}) = \mathrm{softmax}\left(\frac{\mathrm{QK}^{\mathrm{T}}}{\sqrt{\mathrm{d_k}}}\right)\mathrm{V} \tag{4}$$

where Q, K and V are query matrix, key matrix and value matrix respectively. dk is the size of the key vector. This equation shows that the model automatically adjusts to match the importance of the information at each moment. Based on this method, the model can capture the historical conditions that are more important for the current carbon price change, such as the large trading behavior near the performance date, the transmission effect of the energy price surge, and the special volatility range of the policy change expectation, so as to enhance the description ability of the complex market. In the output layer, the time series features obtained by encoding are transformed into the carbon quota price results predicted in the next step.

$$\widehat{\mathrm{P}}_{\mathrm{t+1}} = \mathrm{W_o}\mathrm{H_t} + \mathrm{b_o} \tag{5}$$

where $\widehat{\mathrm{P}}_{\mathrm{t+1}}$ represents the predicted value of carbon emission price at the next moment, $\mathrm{H_t}$ is the overall feature representation result obtained by the Transformer encoder, $\mathrm{W_o}$ and $\mathrm{b_o}$ are the output weight and bias term respectively. Compared with only considering the historical information of a short window, the short-term volatility and long-term impact factors can be considered at the same time, so as to better describe the market price formation mechanism under different performance cycles, different energy cost conditions and different policy conditions. The simulation results can provide reference for analyzing the early warning signals of abnormal market volatility and the price forecast required for future strategy formulation.

4.3 Dynamic Adjustment Optimization Model Based on Deep Reinforcement Learning

In fact, the dynamic regulation of carbon emission permits market is a process of continuous observation, rolling decision-making and continuous modification of strategies in the uncertain environment, which can be better described by modeling it as a Markov decision process. To this end, this paper models the carbon emission permit market regulation problem as a Markov decision process. Let the system state vector at time t be:

$$s_t = [\hat{C}_t, \hat{P}_t, G_t, L_t, R_t, E_t] \tag{6}$$

where $\hat{C}_t$ is the expected carbon emissions; $\hat{P}_t$ is the expected price of carbon allowances; G_t is the gap between quota supply and demand; L_t is a parameter reflecting the liquidity level; R_t is the index of performance pressure; E_t is a series of exogenous variables. Such as electricity price fluctuations, intervention strength and so on. Accordingly, the manager provides parameter change schemes, such as quota allocation proportion, upper and lower limit range of trigger threshold, performance time point, abnormal transaction restriction degree, etc. The operation mode reflects the state of each factor of the market in a simple way: it is transformed into the operable state representation, and the complex management method is transformed into the operable action set, and then forms a unified overall optimization framework.

The reward function design determines the policy learning direction. In this paper, the market stability, transaction efficiency and contract performance order are taken into account to design a real-time reward function.

$$r_t = \beta_1 U_t - \beta_2 \sigma_t - \beta_3 D_t - \beta_4 Z_t \tag{7}$$

where: the profit part of market operation can reflect the increase of trading volume and the improvement of resource allocation in the whole market; σ_t represents the degree of abnormal carbon price fluctuation; D_t represents the performance deviation cost; Z_t represents the market risk penalty factor; Let β_1 to β_4 denote the weight coefficients. The model not only seeks to reduce the price volatility, but also aims to maintain the normal market price level under the premise of stabilizing the market and avoid the market shrinkage caused by excessive intervention.

The soft actor-critic algorithm is used in the algorithm part of this paper. Different from the methods based on fixed rules or certainty, the entropy regularization term is introduced into the objective function of the algorithm to make the algorithm maintain a relatively stable state in terms of revenue maximization and exploration strategy, namely:

$$J(\pi) = \sum_t \mathbb{E}_{(s_t,a_t)\sim\pi} [r_t + \alpha \mathcal{H}(\pi(\cdot\,|s_t)] \tag{8}$$

where π denotes the policy function; $\mathcal{H}(\pi(\cdot\,|s_t)$ is the entropy of the policy; α is the temperature parameter. The introduction of entropy factor in the model can prevent premature convergence to a certain path and ensure the ability to explore and adapt under different market conditions, which is particularly important in the face of the uncertainty and volatility of the carbon market.

In a word, this method integrates emission trend, price information, constraints and risk factors into the same decision space, and uses the iterative process of "state recognition-action generation-reward feed-strategy update" for online policy optimization. Compared with the traditional static rule-dominated method, it is more suitable for solving the nonlinear constraint and multi-objective problem of carbon emissions in the low-carbon development stage. At the same time, it also provides a practical and feasible decision-making reference for us to establish and simulate more systematically.

5 System Implementation and Application Case Analysis

5.1 System Implementation Plan and Technology Stack Design

In order to verify the feasibility and operability of the dynamic adjustment structure of carbon emission market designed in this paper, the data input, model solving, optimization decision, visualization and management control modules are divided into interrelated service components by using service-oriented design pattern to improve the scalability and maintainability of the system. On the whole, this method includes three parts: back-end service unit, front-end interaction unit and deployment and implementation unit, which not only meets the requirements of parallel processing and analysis of multi-source information in carbon trading market, but also facilitates the replacement and upgrading of prediction algorithms, control strategies and human-computer interaction subroutines.

The back-end service layer is the part that implements the core functions of the system, mainly accomplishing data storage, model calling and business processing. The whole system uses Python as the main development language, and develops a synchronous Web API based on FastAPI to receive access to data streams such as pollutant monitoring, transaction data, electricity price and policy. Pandas and NumPy are used for data cleaning, alignment, and feature transformation. The prediction model and deep reinforcement learning algorithm are built on PyTorch for training and inference. Aiming at the characteristics of frequent update and complex field composition of time series data in carbon market, in our system, the structured commercial data is stored in PostgreSQL, and Redis is used to improve the high-frequency state caching effect and the speed of task scheduling, so as to improve the response speed of model use.

In the front-end visualization part, the operation needs of regulators and researchers are mainly considered. The visualization page is designed in Vue 3, and the carbon price trend graph, supply and demand gap graph, performance pressure graph, and adjustment effect comparison graph are displayed combined with ECharts. The front-end interface not only provides the function of market tracking, but also converts the simulation results into easy-to-understand control rules, risk tips and parameter change instructions, so that the abstract and obscure algorithm results are easier to apply to the control strategy. At the same time, the system reserves a rule configuration interface to facilitate dynamic parameter adjustment in accordance with different market system requirements at different stages.

The deployment and operation layer mainly ensures the stable operation of the system in the simulation environment. After each service is containerized, it is unified orchestrated through Docker Compose to reduce the impact of environmental differences on model deployment and interface calls. The simulation end builds carbon market operation scenarios to simulate quota allocation, price fluctuations, compliance progress, and abnormal disturbances, and returns feedback results to the decision-making module to form a closed loop of "data perception - model calculation - strategy execution - result transmission". As shown in Table 3, the system technology stack is configured around data processing, model training, interface services, and visualization display, which can well meet the implementation requirements of this paper's research.

Table 3: Main Technology Stack Design of the System Implementation Plan

Module	Key Technologies	Function Description
Backend Service	Python, FastAPI	Implements asynchronous APIs, strategy invocation, and business logic processing
Data Processing	Pandas, NumPy	Performs data cleaning, feature engineering, and matrix computations
Model Construction	PyTorch	Implements emission prediction, carbon price forecasting, and deep reinforcement learning models
Data Storage	PostgreSQL, Redis	Stores business data and supports high-frequency caching and fast retrieval
Frontend Display	Vue 3, ECharts	Provides market monitoring, chart visualization, and interaction with adjustment results
Deployment & Operations	Docker Compose	Handles container orchestration, service deployment, and simulation environment management

5.2 Case Scenario and Parameter Settings

To test the applicability and stability of the dynamic adjustment system constructed in this paper, this paper bases on a certain provincial carbon emission rights market expansion operation scenario to build a simulation case. The case object covers four key emission control industries: power generation, steel, cement, and chemical. It includes both entities with large emission scales and strong compliance constraints, as well as market participants with high trading activity and high price sensitivity. The purpose of this setting is to try to reflect the real characteristics of "distinct emission differences, inconsistent compliance rhythms, and intertwined price expectations" in the operation of the carbon market under a low-carbon economy. As shown in Table 4, the simulation scenario sets a total of 120 key emission enterprises, and divides them into different types based on industry emission intensity, historical compliance performance, and trading participation degree, in order to observe the response effect of the dynamic adjustment strategy under heterogeneous entities.

Table 4: Main Parameter Settings of the Case Scenario

Parameter Category	Setting	Description
Market Scope	Provincial-level carbon emission trading market simulation scenario	Simulates the operation of an expanded regional carbon market
Industry Type	Power generation, steel, cement, chemical	Covers high-emission and highly sensitive industries
Number of Enterprises	120	Includes entities with different compliance capabilities and trading preferences
Simulation Period	Continuous 12 months	Reflects annual compliance and periodic volatility characteristics
Time Granularity	Daily monitoring, hourly trading	Captures both emission changes and price feedback
Input Data	Emissions, energy prices, trading volume, holdings, policy information, etc.	Constructs a multi-source joint input scenario
Prediction Window	7-day emissions, 24-hour carbon price	Meets medium- and short-term adjustment needs
Strategy Update Frequency	Rolling update every 24 hours	Keeps adjustment rhythm aligned with market changes

We use the most recent year's data as training and test sets and split them into two levels: by day, for trading behavior and price movement vectors; For the regulatory and market motivation variables, we split by hour. In the prediction phase, a typical time window of 30 days is selected for analysis. We input historical emissions, energy consumption, carbon quota stock, buying and selling price and trading volume, gas price, industrial growth index and compliance term policy. In order to enhance the volatility of the system, on the premise of ensuring the rationality of the data, disturbance factors such as quota reduction, energy consumption increase and intensive compliance trading are added. Let the system be tested in a more complex market environment. All the data are standardized and aligned, which is the basic database for model learning and simulation.

In the hyperparameter setting, we set the prediction period of CO2 as 7 days, and the prediction window of CO2 unit price as 1 day. The reset frequency (that is, every day) will re-solve and update an optimal strategy. γ is set to 0.99 in RL model construction, and the experience pool size is set to 1×10^6 DQN. And set batch_size = 256; For the market stability index, factors such as price change rate, trading volume, performance deviation and supply and demand ratio are comprehensively considered to judge. This selection can reflect that the regulation of carbon market does not require high-frequency intervention, and also meets the requirements of policy response time and market response time interval in the implementation process in reality. Based on this case design, we systematically show the process of pollutant monitoring, price prediction, strategy improvement and profit calculation.

5.3 Simulation Results and Optimization Effect Analysis

In order to verify the effectiveness of the online adjustment mechanism proposed in this section, three comparison strategies are set up for experiments, which are quota regulation according to fixed threshold and heuristic rules respectively. The rolling optimization method is used to obtain the MILP strategy and DRL strategy of the phased adaptation scheme. All three methods are run in the same environment (including the same simulation environment), using the same data source and constraints to ensure their comparability.

From the perspective of cumulative net income changes, the DRL strategy demonstrated a stronger ability to continuously increase gains throughout the simulation period. As shown in Figure 3, on the first day of the simulation, the cumulative net income of the benchmark strategy, the MILP strategy, and the DRL strategy was 180,000 yuan, 210,000 yuan, and 230,000 yuan respectively, and the differences were not obvious; after the 10th day, the differences began to widen, and the cumulative net incomes of the three strategies increased to 1,810,000 yuan, 2,140,000 yuan, and 2,460,000 yuan respectively; by the 20th day, this figure further expanded to 3,510,000 yuan, 4,280,000 yuan, and 5,070,000 yuan; by the end of the typical 30-day simulation window, the cumulative net income of the benchmark strategy was 508,000 yuan, the MILP strategy was 621,000 yuan, and the DRL strategy reached 752,000 yuan. Based on this calculation, the DRL strategy outperformed the benchmark strategy by 244,000 yuan, an increase of approximately 48.0%; and outperformed the MILP strategy by 131,000 yuan, an increase of approximately 21.1%. This result indicates that the deep reinforcement learning strategy can continuously adjust the adjustment intensity during the performance period, price fluctuations, and changes in trading expectations, and its advantage in gains does not come from a single point of accidental optimization, but is gradually accumulated through multiple rounds of feedback.

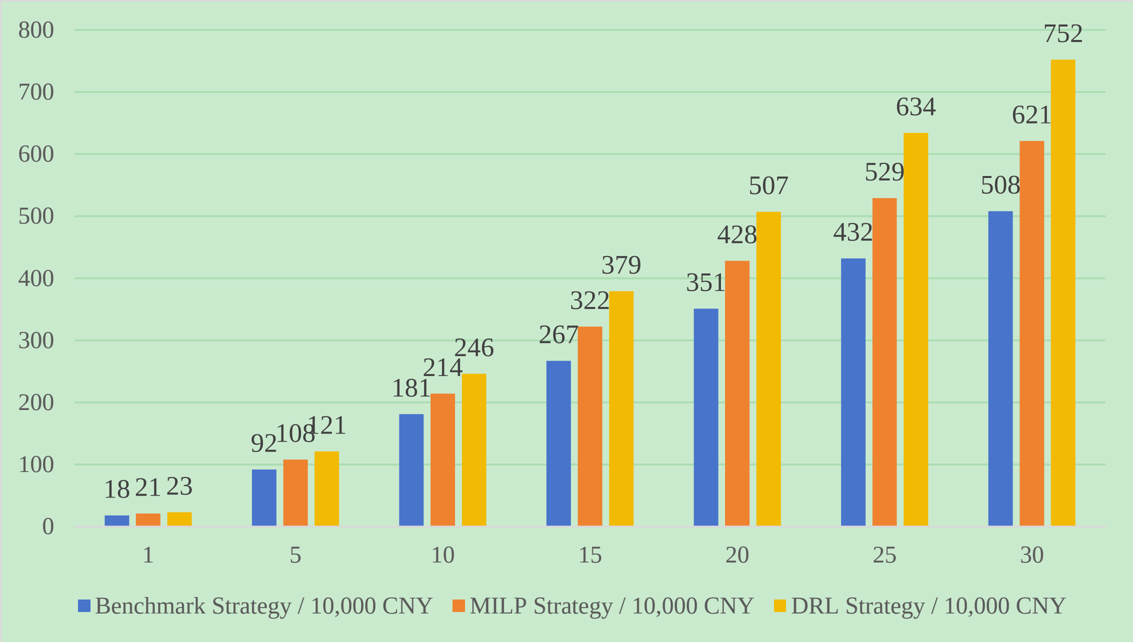

Figure 3: Cumulative Net Profit Change Curve of Typical Simulation Period under Different Strategies

From the perspective of market operation quality, the DRL strategy also performs exceptionally well in suppressing fluctuations and improving compliance order. As shown in Figure 4, under the benchmark strategy, the carbon price volatility rate was 18.6%, the compliance deviation rate was 9.4%, the number of abnormal fluctuations reached 17 times, and the average adjustment response duration was 42 minutes, indicating that although the fixed rules are easy to implement, their adaptability to complex disturbances is relatively weak. The relevant indicators of the MILP strategy have improved. The carbon price volatility rate dropped to 13.2%, the compliance deviation rate decreased to 6.1%, the number of abnormal fluctuations decreased to 10 times, and the average response duration shortened to 18 minutes. This shows that the rolling optimization has a certain role in stabilizing the market. However, this method still relies heavily on prediction accuracy. When external disturbances increase, the adjustment actions are prone to lag. In contrast, the DRL strategy further reduced the carbon price volatility rate to 8.7%, a decrease of 9.9 percentage points compared to the benchmark strategy and 4.5 percentage points compared to the MILP strategy; the compliance deviation rate dropped to 3.2%, only 34.0% of the benchmark strategy; the number of abnormal fluctuations decreased to 4 times, a decrease of 76.5% compared to the benchmark strategy; the average adjustment response duration shortened to 6 minutes, 12 minutes less than the MILP strategy.

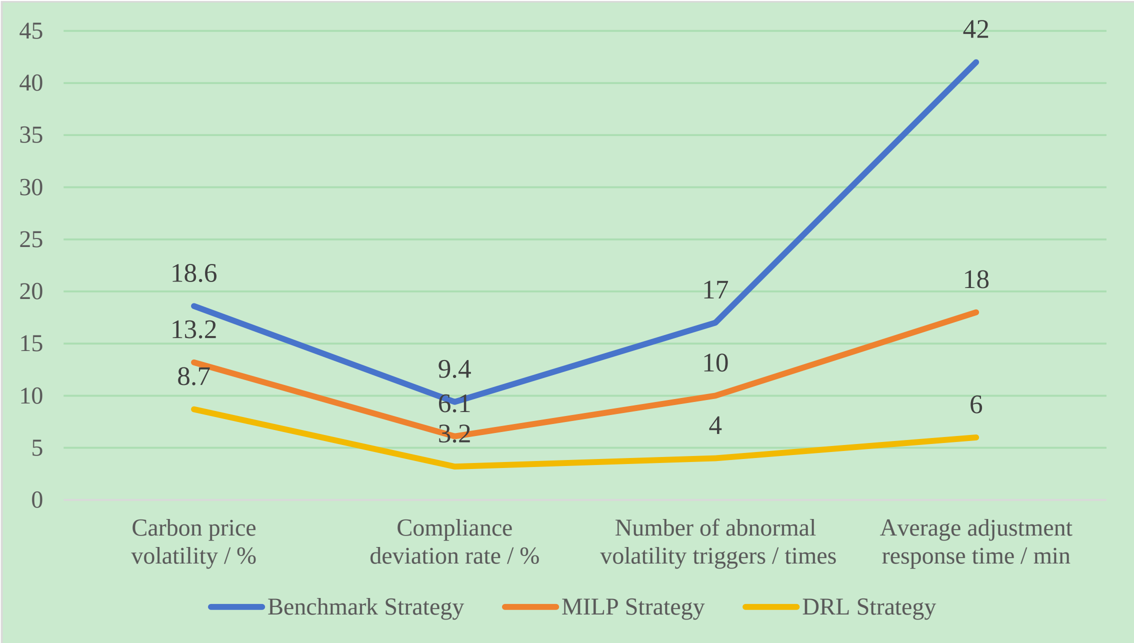

Figure 4: Comparison of key market operation indicators under different strategies

The comprehensive simulation results show that the benchmark strategy is simple to implement but prone to causing excessive adjustment and cumulative fluctuations; the MILP strategy can improve the level of phased optimization, but is sensitive to prediction errors; the DRL strategy proposed in this paper achieves the best results in terms of net income, price stability, control of performance deviation, and response efficiency. This indicates that coupling emission monitoring, carbon price prediction with reinforcement learning decision-making can help enhance the forward-looking and adaptability of the dynamic regulation of the carbon emission rights market, and also verifies the application value of the closed-loop regulation framework in complex market environments.

6 Discussion

The simulation results show that the dynamic adjustment framework driven by intelligent computing has a relatively stable application advantage in the carbon emission rights market. In terms of operational effectiveness, the DRL strategy achieved a cumulative net profit of 7.52 million yuan at the end of the 30 day simulation period, significantly higher than the MILP strategy's 6.21 million yuan and the benchmark strategy's 5.08 million yuan; At the same time, the carbon price volatility dropped to 8.7%, the compliance deviation rate dropped to 3.2%, and the number of abnormal fluctuations triggered was only 4 times, indicating that the system is not simply relying on strengthening intervention to achieve surface stability, but has formed a more reasonable balance between increasing returns, suppressing risks, and maintaining compliance order. This result is not caused by a local improvement in the accuracy of a model, but by the integration of emission monitoring, pricing prediction, and decision control into a feedback loop, which transitions from lagged response to anticipatory response.

Compared with traditional rule-based methods, the advantages of the proposed method are that it can adapt to complex situation disturbances. Generally, the fixed threshold is adopted or determined by experience, and it cannot automatically respond to large-scale transactions in the performance period, simultaneous increase in energy prices and policy changes. Although the MILP method has strong constraint expression ability, it is extremely sensitive to forecast errors. When the market situation deviates from the preset situation, its correction effect will quickly fail. The deep reinforcement learning method learns the mapping relationship between the market state and the control action in continuous interaction, which can continuously improve the control strength in the iterative process. So they show greater adaptability. This means that the optimization of the carbon emission rights market should not be limited to quota allocation or price interpretation, but should shift towards integrated governance of "perception judgment decision-making feedback".

This study still has certain limitations. Firstly, although multiple industry entities and disruptive events have been introduced in the case scenario, there is still a gap between the simulation environment and the real market, especially in terms of performance under extreme policy shocks and abnormal data conditions, which still needs further testing. Secondly, deep reinforcement learning models are sensitive to the size of training samples and parameter settings, resulting in relatively high initial training costs. Third, although the model can output better strategies, it still needs to enhance the interpretable expression in the regulatory practice, so that the policy recommendations can be more easily understood and adopted by the system executors. From this perspective, further research can focus on cross regional market linkage, multi scenario robust training, and interpretable decision interfaces.

7 Conclusion and Prospect

Combined with the characteristics of fragmentation, volatility and lag of carbon trading market in low-carbon economy, this paper designs a carbon trading market regulation system based on intelligent algorithm optimization, and conducts research and analysis from four aspects of mechanism analysis, system framework, key models and simulation verification. Conclusion: The dynamic regulation of carbon trading market should take a comprehensive approach, not just a single quota regulation or price intervention. A closed-loop system of emissions monitor-price forecase-strategy decision-feedback effect should be established. At the same time, the carbon emission monitoring and prediction model, the carbon quota price change prediction model, and the adaptive tuning decision model based on deep reinforcement learning are integrated into a unified platform to realize the function of generating control schemes from the understanding of the market, which changes the carbon market regulation from experience-based to data-based. The simulation results further validated the effectiveness of the framework. Compared with the benchmark strategy and MILP strategy, the DRL strategy shows better performance in cumulative net income, carbon price fluctuation control, performance deviation suppression, and adjustment response efficiency, indicating that intelligent computing methods have strong adaptability and foresight in dealing with high volatility, strong correlation, and multi-objective constraints in the carbon market. This result also indicates that the optimization of the carbon emission rights market in the context of a low-carbon economy should not only be limited to institutional design and post evaluation, but also requires the use of computer technology to enhance real-time identification and dynamic correction capabilities in the market operation process, thereby enhancing the accuracy, continuity, and synergy of regulation.

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