International Journal of Data Science

ISSN online: 2053-082X - ISSN print: 2053-0811
https://www.inderscience.com/ijds

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DOI: 10.1504/IJDS.2025.10072254

Article History:

Received:	11 January 2025
Last revised:	26 May 2025
Accepted:	19 June 2025
Published online:	16 January 2026

Green logistics network optimisation and carbon emission reduction using blockchain technology

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Abstract: This paper explores green logistics network optimisation and carbon emission reduction through blockchain technology, IoT, and big data. A blockchain-based logistics model was developed, incorporating smart contracts for automated carbon management and IoT devices for real-time emission monitoring. Big data analysis enabled logistics path optimisation. Experimental results showed that using ant colony optimisation reduced transportation time by 20%, fuel consumption by 15%, and carbon emissions by 18%. The proposed method enhances logistics efficiency and reduces environmental impact, offering practical solutions and theoretical support for sustainable logistics networks.

Keywords: blockchain technology; green logistics; carbon emissions; path optimisation; smart contracts; IoT; Internet of Things; ACO; ant colony optimisation.

Reference to this paper should be made as follows: Liu, S. and Wang, B. (2025) 'Green logistics network optimisation and carbon emission reduction using blockchain technology', *Int. J. Data Science*, Vol. 10, No. 7, pp.73–92.

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1 Introduction

In the face of escalating global warming and environmental pollution, reducing carbon emissions has become a universal goal across industries. Blockchain technology, known for its decentralisation, immutability, and high transparency, is increasingly popular in logistics network management. Traditional methods suffer from issues such as data transparency, trust mechanisms, and information delays, leading to poor carbon emissions management (Kumar et al., 2021). Blockchain can mitigate operational risks and enhance the transparency and credibility of logistics networks, enabling real-time monitoring and management of carbon emissions and ensuring data authenticity (Issaoui, 2020). This paper proposes a green logistics network optimisation method based on blockchain, integrating IoT and big data analysis. The method monitors and manages carbon emissions in real-time through a blockchain logistics network model and verifies its effectiveness experimentally. The findings promote blockchain's application in green logistics, offering theoretical support and technical solutions for the industry's low-carbon transformation, and providing valuable references for researchers in related fields.

Green logistics network optimisation methods use the Internet of Things (IoT), blockchain and big data analysis to improve the transparency, credibility and efficiency of traditional logistics management data. The blockchain-based logistics network model also improves the transparency and credibility of data. Smart contracts are designed to achieve automated carbon emission management and carbon credit trading mechanisms, reducing human intervention and operational risks, and ensuring real-time recording and management of carbon emission data. IoT devices such as GPS locators, temperature sensors, and fuel sensors are used for real-time monitoring and recording of key parameters in logistics processes, ensuring the timeliness and accuracy of data, and providing a reliable data foundation for subsequent carbon emission management and optimisation. Big data analysis technology identifies carbon emission sources and optimisation spaces in logistics networks through clustering analysis, regression analysis, and time series analysis, and proposes methods for optimising logistics paths and transportation scheduling. The experimental results show that after adopting the method proposed in this paper, transportation time is reduced by about 20%; fuel consumption is reduced by 15%; carbon emissions are reduced by 18%. The method presented in this paper not only validates its effectiveness, but also provides strong support for the practical application of green logistics networks, providing new technical means and theoretical support for achieving green logistics and sustainable development goals.

2 Related work

There is a close relationship between optimising green logistics networks and reducing carbon emissions, which mutually promote the achievement of sustainable development and environmental protection goals. Dzwigol et al. (2021) proposed that circular economy is an innovative logistics organisation method, identified the obstacles to its implementation, and suggested improving the efficiency and environmental safety level of green logistics management through organisational economic mechanisms to achieve sustainable development. Al-Minhas et al. (2020) developed an integrated model by conducting a comprehensive review of existing literature on green human resource management and sustainable green logistics, identifying key driving factors for sustainable green logistics and corporate environmental management, and achieving balanced performance in social and environmental well-being. Tian et al. (2023) proposed that in the context of increasingly severe environmental problems, low-carbon development has become an inevitable choice. By constructing the overall structure of multi-criteria decision-making (MCDM) technology in the fields of green logistics and carbon emission reduction, relevant improvement suggestions and research directions were proposed. Agyabeng-Mensah et al. (2021) found through a survey data analysis of 152 manufacturing small and medium-sized enterprise managers in Ghana that green logistics practices significantly improved social performance, financial performance, and green competitiveness, and played a mediating role between green human capital and these performance indicators, providing new insights into the role of green human capital in the implementation of green logistics. Khan (2019) found that logistics operations lacking green technologies and low-carbon practices mainly rely on fossil fuels, leading to high carbon emissions. He suggested improving environmental sustainability by reducing poverty and promoting green logistics technologies and low-carbon practices. However, these studies mostly focus on the application of a single technology, failing to fully integrate multiple technical means for comprehensive optimisation, and insufficient consideration is given to data transparency and system complexity in practical applications.

Blockchain technology, with its characteristics of decentralisation, openness, and security, provides higher transparency and traceability for green logistics networks. Zhu et al. (2024) proposed that blockchain supported carbon offset information and transportation options can enhance consumer trust in retailers and logistics service providers, and concluded that blockchain can effectively reduce carbon emissions in the logistics process. Koh et al. (2020) proposed that blockchain technology can revolutionise data and business process management, emphasised the application demonstration of blockchain in supply chain, manufacturing, and service industries, and pointed out the need for close coordination between transportation infrastructure and digital infrastructure to enhance trade relations and transform global supply chains. Under the carbon tax policy, Manupati et al. (2020) proposed that blockchain technology can revolutionise supply chain processes by monitoring supply chain performance, optimising emission levels and operating costs, and achieving better supply chain effects, providing support for policy makers and supply chain executives. Ahmed et al. (2022) explained the important role of blockchain and artificial intelligence in intelligent and sustainable IoT applications, proposed a conceptual framework that combines cloud computing, IoT devices, and artificial intelligence, and used blockchain technology to store results in decentralised cloud storage, thereby promoting the development of various applications.

Humayun et al. (2020) explored the potential of IoT and blockchain technology in smart logistics and transportation, and proposed a layered framework that integrates IoT and blockchain technology to provide intelligent logistics and transportation systems, demonstrating their application contributions in logistics and transportation. However, most of these studies remain at the theoretical level, lacking practical applications and experimental verification, and there are shortcomings in system integration and operational complexity.

3 Experimental data

3.1 Data sources and collection

The experimental data sources of this paper mainly include three parts: IoT devices, blockchain networks, and logistics management systems. These data are sourced from actual logistics operations, covering information on transportation paths, cargo status, fuel consumption, and other aspects, ensuring the comprehensiveness and authenticity of the data (Samir et al., 2019). In order to verify the effectiveness of the research method, this paper records 5000 data records.

During the data collection process, the sampling frequency of the GPS locator and fuel sensor is set to once every 15 min, and the sampling frequency of the temperature sensor is once every 5 min to balance the real-time nature of the data and the storage pressure. For abnormal data (such as sensor signal loss or sudden value change), the sliding window mean filter method is used for cleaning, and outliers are eliminated by the triple standard deviation principle.

IoT devices are deployed at various nodes in the logistics network to monitor and record key parameters in real-time during the logistics process. GPS locator records the real-time position, driving path, and transportation time of the vehicle; temperature sensors monitor the environmental temperature of goods during storage and transportation; fuel sensors measure the fuel consumption of the vehicle during transportation. Providing detailed energy usage data through sensors is crucial for calculating carbon emissions (Wang et al., 2019). The specific data is shown in Table 1.

Table 1 IoT device data

Vehicle ID	*Timestamp*	*Latitude*	*Longitude*	*Temperature* (□)	*Fuel consumption* (L)
V001	2024/5/1 8:00	34.0522	–118.2437	20.5	10.2
V002	2024/5/1 8:15	36.1699	–115.1398	22	9.8
V003	2024/5/1 8:30	35.6895	139.6917	19	10
V004	2024/5/1 8:45	40.7128	–74.006	18.5	11.2
…	…	…	…	…	…
V5000	2024/5/15 18:30	37.7749	–122.4194	21	9.5

In Table 1, ‘vehicle ID’ represents the unique identifier of a specific vehicle; the ‘timestamp’ records the specific time of data collection; ‘latitude’ and ‘longitude’ display the specific geographic location of the vehicle; ‘temperature’ monitors the environmental temperature during storage or transportation; the ‘fuel consumption’ records the fuel usage of the vehicle during that time period.

Blockchain network data is collected by recording every transaction and event, ensuring the authenticity and immutability of the data. Specifically, the operation records of each logistics node, including the loading and unloading of cargoes, transportation time, and cargo status, are recorded on the blockchain. The data on transportation paths and tool types records detailed information for each transportation path, including the type of transportation tool used, which can help analyse the impact of different transportation methods on carbon emissions. Energy consumption data is integrated with fuel sensor data from IoT devices to record fuel usage and carbon emissions during each transportation process. The transparency and immutability of these data are guaranteed through blockchain technology, ensuring that every record is trustworthy (Liang et al., 2020). The specific data is shown in Table 2.

Table 2 Blockchain network data

Transaction ID	*Vehicle ID*	*Timestamp*	*Operation type*	*Transportation mode*	*Fuel consumption* (L)	*Carbon emission* (kg)
T001	V001	2024/5/1 8:00	Loading	Truck	10.2	26.5
T002	V002	2024/5/1 8:15	Shipping	Train	9.8	25.2
T003	V003	2024/5/1 8:30	Unloading	Truck	10	26
T004	V004	2024/5/1 8:45	Loading	Train	11.2	28.4
…	…	…	…	…	…	…
T5000	V5000	2024/5/15 18:30	Unloading	Truck	9.5	24

In Table 2, ‘transaction ID’ represents a unique identifier for a specific transaction; ‘vehicle ID’ represents the vehicle performing the operation; the ‘timestamp’ records the specific time of the transaction; ‘operation type’ displays the specific content of logistics operations; the ‘transportation mode’ records the transportation method used; ‘fuel consumption’ records the amount of fuel used in the operation; the ‘carbon emission’ is the carbon dioxide emission calculated based on fuel consumption.

Logistics management system data is relevant data extracted from existing logistics management systems. These data include order ID, type of cargoes, weight, destination, transportation distance, and estimated transportation time. As shown in Table 3, these data provide the basis for the overall analysis of the logistics network (Winkelhaus and Grosse, 2020).

In Table 3, ‘Order ID’ is the unique identifier of the logistics order; ‘Cargo Type’ indicates the category of the transported cargo; ‘Weight’ indicates the total weight of the cargo; ‘Destination’ indicates the final destination of the cargo; ‘Transportation Distance’ indicates the transportation distance from the starting point to the destination; ‘Estimated Transportation Time’ indicates the time required to complete the transportation.

Table 3 Logistics management system

Order ID	*Cargo type*	*Weight (kg)*	*Destination*	*Transportation distance (km)*	*Expected transportation time (h)*
O001	Electronics	500	Los Angeles	1200	10
O002	Food	300	Las Vegas	400	4
O003	Clothing	200	Tokyo	1500	12
O004	Furniture	800	New York	2500	20
…	…	…	…	…	…
O5000	Medicine	1000	San Francisco	3000	25

It should be pointed out that the experimental data of this study mainly comes from IoT devices, blockchain networks and logistics management systems in a simulated environment. Although the integrity and reliability of the data are ensured through precise alignment and merging, it still needs to be further verified in combination with the dynamic characteristics of actual logistics scenarios. For example, unexpected road conditions, equipment failures or data heterogeneity problems that may exist in a real transportation environment may place higher requirements on the robustness of the model. Subsequent research will obtain real business data through cooperation with logistics companies to enhance the practicality and adaptability of the method.

3.2 Data processing

3.2.1 Data alignment

This paper accurately aligns data from different sources. Data alignment involves operations such as time window alignment, timestamp normalisation, and key field matching (Katoh et al., 2019). This includes synchronising records from different sources based on key fields such as time and vehicle ID. Timestamp normalisation converts all timestamps to ISO 8601 format, ensuring to second precisely. Key field matching uses fields such as vehicle ID to ensure that related data is aligned at the same point in time. In logistics data, vehicle ID uniquely identifies a vehicle. When timestamps do not match exactly, time window alignment allows records with small time differences to be treated as simultaneous. This can solve the problem of inconsistent timestamps caused by different data collection frequencies while ensuring data continuity (Biancalani et al., 2021).

3.2.2 Data merge

Data merge refers to the integration of aligned data from different data sources to form a comprehensive dataset. The specific operations include determining the merge key, merging data sources, handling missing values, and constructing a comprehensive data table.

The merge key is confirmed to select the key fields for merging, ensuring consistency across all data sources to ensure that the data can be merged correctly. Data sources are merged using the outer join merge method, merging data from different sources together to ensure that each record contains relevant information from all data sources. The external connection method can ensure that even if some records are missing from a certain data source, records from other data sources are not lost (Gruber et al., 2019).

After merging, there are missing values. If there are too many missing values, the direct deletion is selected. If there are fewer missing values, the mean is selected to fill in and ensure data integrity. The specific formula is shown in formula (1).

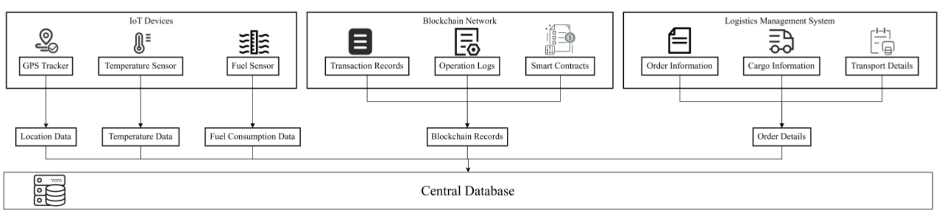
$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Among them, $\bar{x}$ is the mean of variable x; n is the number of non-missing values; x_i is the i th non missing value.

Based on the above information, a comprehensive data table is constructed, which should include all necessary fields: vehicle ID, timestamp, latitude and longitude, temperature, fuel consumption, operation type, cargo status, transportation method, carbon emissions, order ID, cargo type, weight, destination, transportation distance, and estimated transportation time. It is necessary to ensure that each record provides comprehensive logistics information.

This paper conducts experiments on IoT devices, blockchain networks, and logistics management systems. These data are collected through different channels and ultimately integrated into a central database for optimising green logistics networks and managing carbon emissions, as shown in Figure 1.

Figure 1 Data integration process



IoT devices include GPS locators, temperature sensors, and fuel sensors, which monitor and record key parameters such as vehicle location, environmental temperature, and fuel consumption in real-time; the blockchain network ensures the authenticity and immutability of data by recording every transaction and operation log, as well as executing smart contracts; the logistics management system provides detailed order information, cargo information, and transportation details. All data flows to the central database for integration and analysis, forming a comprehensive and accurate logistics dataset, providing solid data support for subsequent analysis and optimisation.

4 Optimisation of green logistics network

4.1 Construction of blockchain logistics network model

This paper studies a green logistics network optimisation method that combines blockchain technology, the IoT, and big data analysis technology. The construction of a blockchain logistics network model includes path optimisation and scheduling. Through path optimisation and reasonable design of scheduling plans, transportation distance and time are reduced, thereby reducing fuel consumption and carbon emissions.

In terms of path optimisation, this paper uses the vehicle routing problem (VRP) model as the basis to optimise the transportation path, with the objective function of minimising the total transportation distance or total transportation time (Mor and Speranza, 2022). The formula is as follows.

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} \tag{2}$$

In the formula (2), the transportation cost from node i to node j is represented by c_{ij}, and x_{ij} is a binary variable.

ACO is a common heuristic search algorithm that randomly distributes a certain number of ants on the path, and each ant represents a solution. Each ant selects the next path based on the pheromone concentration and heuristic information on the path. When the ant completes a path selection, it releases pheromones on the path, and the pheromone concentration decreases over time. Therefore, this paper uses ACO to solve the combinatorial optimisation problem in scheduling planning (Singh et al., 2020), as shown in formula (3):

$$\tau_{ij} = (1-\rho)\tau_{ij} + \Delta\tau_{ij} \tag{3}$$

In formula (3), the concentration of pheromones on path $i \to j$ is τ_{ij}; ρ is the volatility coefficient of pheromones; $\Delta\tau_{ij}$ is the increment of pheromones.

Finally, path selection and pheromone update operations are repeated until the optimal path is found or the maximum number of iterations is reached.

4.2 Smart contracts

A smart contract is an automated program that automatically executes protocol terms when predetermined conditions are met. Smart contract design is used to achieve carbon emission calculation and carbon credit trading, which helps to reduce carbon emissions. The smart contract in this paper includes two aspects: carbon emission calculation contract and carbon credit trading contract.

The carbon emission calculation contract automatically calculates carbon emissions based on fuel consumption data during transportation and records them on the blockchain. Smart contracts ensure transparency and immutability of all operations (Wang and Ouyang, 2019). The formula for calculating carbon emissions is as follows:

$$X = W \times C \tag{4}$$

Among them, X represents carbon emissions (kg); W is the fuel consumption (L); C is the carbon emission factor (kg/L). The carbon emission factor is determined based on the type of fuel, and the factor varies for different fuels. The carbon emission factor for diesel is 2.68 kg/L.

Carbon credit trading contracts are automatic carbon credit transactions based on carbon emissions, incentivising logistics participants to adopt low-carbon transportation methods. The carbon credit trading mechanism enhances the environmental awareness and enthusiasm of logistics participants by rewarding low-carbon emission operations.

In the specific implementation of the carbon credit trading mechanism, the allocation of carbon credits is based on the difference between the baseline emissions of the transportation task and the actual emission reduction. The smart contract automatically triggers the issuance and settlement of carbon credits by real-time monitoring of carbon emission data, forming a positive incentive cycle. Experiments have shown that this mechanism has increased the selection rate of low-carbon transportation routes, verifying its guiding role in the behaviour of logistics participants.

4.3 Carbon emission management

This paper adopts a carbon emission calculation method based on fuel consumption, which monitors and records the fuel consumption of vehicles in real-time through IoT devices, and accurately calculates the carbon emissions of each transportation segment. Fuel sensors measure the fuel consumption of each vehicle and record it in IoT devices. These IoT devices record carbon emissions on the blockchain, making the data transparent and reliable. Blockchain technology ensures the immutability and high transparency of data.

Smart contracts can automatically manage carbon emission data, achieving real-time monitoring and management of carbon emissions. Smart contracts are executed on the blockchain to ensure the immutability of carbon emission data. The carbon credit trading mechanism is implemented to incentivise logistics participants to reduce carbon emissions. Carbon credit trading enhances the environmental awareness and enthusiasm of logistics participants by rewarding low-carbon emission operations.

4.4 Big data analysis

4.4.1 Data analysis and mining

Big data analysis plays a crucial role in the optimisation of green logistics networks in this paper. Through big data analysis technology, transportation paths, fuel consumption, and carbon emissions data in logistics networks are analysed. Cluster analysis, regression analysis, and time series analysis are used to explore potential patterns and patterns in logistics data. Cluster analysis is used to identify similar transportation paths and operational patterns in logistics networks. The K-means clustering algorithm is used to classify transportation paths into multiple classes and analyse the transportation characteristics of different classes (Zhu et al., 2024; Wang et al., 2024). The formula is shown in formula (5).

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} \left\| x_j^{(i)} - \mu_i \right\|^2 \tag{5}$$

Among them, k is the number of clusters; $x_j^{(i)}$ is the j th data point of class i ; μ_i is the centre of class i .

Regression analysis is used to establish a relationship model between transportation time and fuel consumption. The linear regression model is used to predict fuel consumption, as shown in formula (6) (Maulud and Abdulazeez, 2020; Chen et al., 2024).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \epsilon \tag{6}$$

In the above formula, y represents the fuel consumption, and x_i is the influencing factor.

Time series analysis is used to predict future transportation demand and carbon emission trends. The autoregressive integrated moving average (ARIMA) model is used for time series prediction (Lai and Dzombak, 2020), as shown in formula (7).

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \tag{7}$$

Among them, y_t is the predicted value of time t; α is a constant term; β_i is the autoregressive coefficient; θ_i is the moving average coefficient; ϵ_t is the error term.

4.4.2 Path optimisation and scheduling improvement

The optimisation and improvement of this paper are based on data analysis results, improving transportation paths and scheduling plans, reducing transportation distance and time. The combination of optimisation algorithms and big data analysis technology continuously improves the operational efficiency of logistics networks. Using real-time data analysis and dynamic optimisation techniques, transportation paths and scheduling plans are adjusted in real-time to ensure the efficient operation of the logistics network.

4.4.3 Performance evaluation and optimisation

Based on the evaluation of logistics performance under different optimisation strategies, including transportation time, fuel consumption, and carbon emissions, the effects of different strategies are compared to determine the optimal logistics network operation plan. According to the analysis results, the logistics strategy is adjusted and optimised to ensure the optimal operation of the logistics network (Ismadiyorov and Sotvoldiyev, 2021; Ran et al., 2024).

5 Experiments

5.1 Experimental environment

In order to verify the effectiveness of the green logistics network optimisation method in this paper, testing and evaluation are conducted in the following experimental environment. In terms of hardware environment, the server is configured with an Intel Xeon E5-2680 v4 CPU, 2.4 GHz, 128 GB of memory, and 2 TB of solid-state drive storage, ensuring sufficient computing power and storage space. IoT devices include GPS locators, temperature sensors, and fuel sensors installed on logistics vehicles, which are used to collect real-time vehicle location, environmental temperature, and fuel consumption data. Blockchain nodes are distributed in multiple geographical locations and run in Docker containers, ensuring the distributed and decentralised characteristics of the network while ensuring the independence and security of nodes.

In terms of software environment, the operating system chooses a stable Linux distribution, Ubuntu 20.04 LTS, to ensure the stability and compatibility of the experimental environment. The blockchain platform adopts Ethereum and writes smart contracts using Solidity language to achieve carbon emission calculation and carbon credit trading. The database uses MySQL to store consolidated data, providing reliable data management and query capabilities. The data analysis tool uses Python programming language, combined with libraries such as Pandas, Numpy, Scikit-learn, Pytorch, and Matplotlib, to implement the application of data analysis and path optimisation algorithms. The optimisation algorithm mainly uses ant colony algorithm to optimise and schedule VRP. In terms of network environment, IoT devices transmit data to central servers through 4G networks to ensure the timeliness and accuracy of data. Blockchain nodes synchronise and exchange data through the internet to ensure the security and reliability of the blockchain network.

It should be pointed out that there is an initial cost investment for the deployment of blockchain nodes and the hardware upgrade of IoT devices. Taking the experimental environment of this paper as an example, the Docker container of a single blockchain node requires a cloud service fee of about US$200 per year, and the hardware cost of installing GPS and fuel consumption sensors on each vehicle is about US$500. However, the economic benefits obtained through carbon credit trading (calculated at US$0.1 for every 1 kg CO_2 emission reduction) can cover the initial investment in about 18 months, forming a sustainable economic closed loop. In the future, the deployment cost can be further reduced by optimising the lightweight node design.

In the experiment, the average block generation time of the blockchain network built on Ethereum was 12 s, and the throughput reached 150 transactions per second (TPS), which is higher than the Hyperledger Fabric (about 100 TPS) commonly used in traditional supply chain systems. In addition, the median execution time of smart contracts was 8.3 ms, which verified the feasibility of the system in high-frequency logistics data processing. By adjusting the consensus mechanism (such as introducing PoA instead of PoW), it is expected that the performance will be further improved in the future to support larger-scale deployment.

5.2 Experimental parameter settings

This paper provides detailed settings for the experimental parameters. For path optimisation, the parameter settings of the ant colony algorithm include 30 ants, a pheromone volatility coefficient of 0.5, a pheromone increment of 1.0, a heuristic factor of 2.0, and a maximum number of iterations of 500. As a comparison, the genetic algorithm parameters are set to a population size of 50, a crossover probability of 0.8, a mutation probability of 0.2, and a maximum number of iterations of 1000. In terms of carbon emission calculation, real-time fuel consumption data is collected through IoT devices. The carbon emission factor of diesel is 2.68 kg/L, and the carbon emission factor of gasoline is 2.31 kg/L. The execution frequency of smart contracts is to execute immediately after each transportation task is completed, and the carbon credit trading rule is to obtain 1 unit of carbon credit for every 1 kg reduction in carbon emissions. In terms of data analysis, K-means clustering algorithm is used for clustering analysis, and the number of clusters is set to 5; the regression model adopts linear regression, and the characteristic variables include transportation time, transportation distance, and cargo weight; the use of ARIMA model in time series analysis provides a solid foundation for verifying the effectiveness of green logistics network optimisation methods.

5.3 Comparison of different experimental models

In order to evaluate the effectiveness of different path optimisation models in green logistics network optimisation, this paper compares traditional VRP models, ant colony algorithm (ACO) models, and genetic algorithm (GA) models (Sun et al., 2020). A detailed comparison of the different experimental models on a number of dimensions, including path optimisation efficiency, carbon emission calculation accuracy, data processing capability, data transparency, and system scalability, is presented in Table 4.

Table 4 Comparison of different models

Indicator	*Traditional VRP model*	*ACO model (Based on VRP)*	*GA model (Based on VRP)*
Path opt. efficiency (POE)	Low efficiency	High efficiency, suitable for complex paths	High efficiency, suitable for complex paths
Carbon emission accuracy (CEA)	Low accuracy	High accuracy with real-time data integration	High accuracy with real-time data integration
Data processing (DP)	Limited, manual handling	High automation, handles large-scale data	High automation, handles large-scale data
Data transparency (DT)	Moderate, partially manual	High transparency, blockchain-based	High transparency, blockchain-based
Algorithm adaptability (AA)	Poor adaptability	Dynamic adjustment, good adaptability	Dynamic adjustment, good adaptability
Smart contract integration (SCI)	Not supported	Supported, automates carbon emission and credit trading	Supported, automates carbon emission and credit trading

In Table 4, traditional VRP models have low POE and CEA, limited DP capabilities, mainly relying on manual processing, moderate (DT, poor AA, and do not support SCI. In contrast, ant colony algorithm and genetic algorithm models perform well in path optimisation efficiency and carbon emission accuracy, can handle large-scale data, have high automation, high data transparency, support smart contract integration, and can dynamically adjust to different transportation scenarios. They are more suitable for large-scale systems and can significantly improve the optimisation effect of green logistics networks.

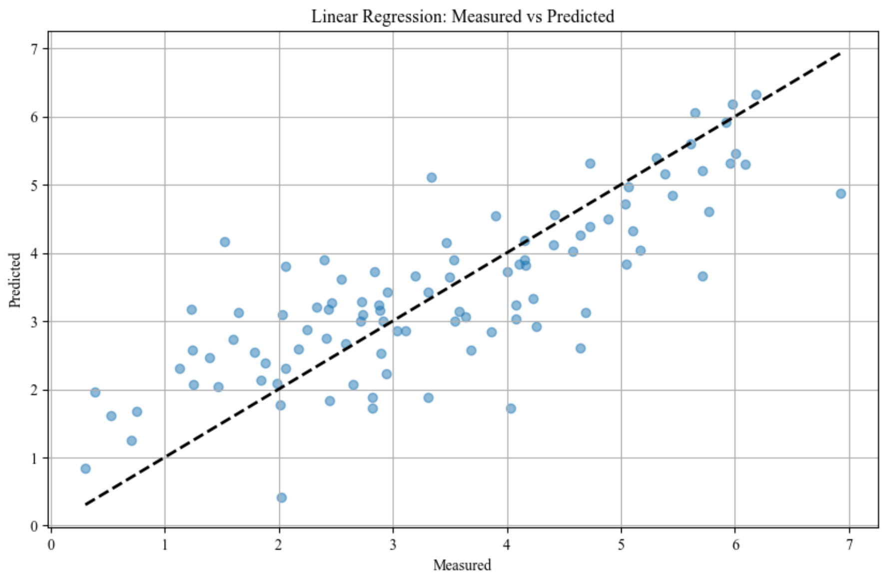
In order to further verify the superiority of the ant colony algorithm, the subsequent research plan of this paper introduces emerging algorithms such as reinforcement learning for comparison. Reinforcement learning's ability to adapt to complex environmental changes through dynamic strategy adjustment may provide new optimisation perspectives in path optimisation efficiency and carbon emission control. By comparing the performance of ACO, GA and RL in multi-objective optimisation, we can more comprehensively evaluate the applicability of different algorithms in green logistics networks and provide more targeted technical choices for practical applications.

6 Results

6.1 Predicting logistics data trends

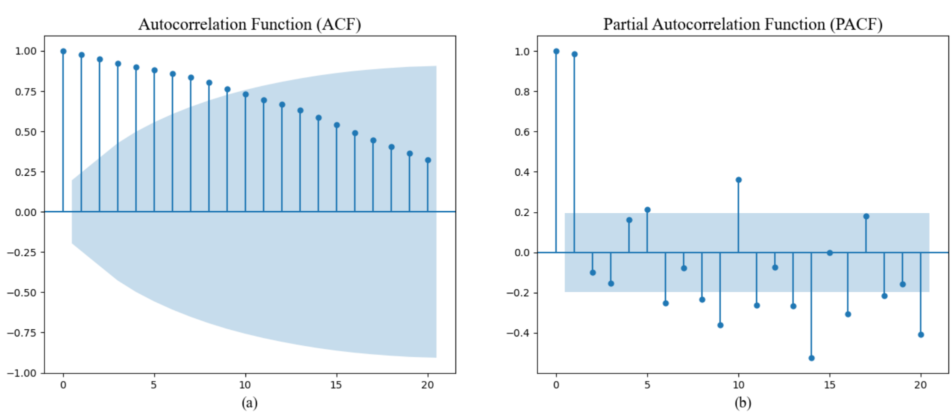
This paper conducts a series of analyses on the collected data to verify the effectiveness of the experimental method to understand the relationship between key logistics variables and predict future trends. Figure 2 shows the results of linear regression and time series analysis, which uses transportation time, transportation distance and cargo weight as feature variables to predict fuel consumption.

Figure 2 Scatter plot of fuel consumption prediction (see online version for colours)



In Figure 2, a scatter plot of the relationship between the linear regression model's predicted fuel consumption and the characteristic variables is shown. Ideally, the predicted values are exactly the same as the actual values, but the clustering of points close to the diagonal line indicates a high correlation between the predicted and actual values. This shows that the linear regression model can accurately predict the relationship between transportation time, transportation distance, and cargo weight.

Figure 3 Data analysis (see online version for colours)



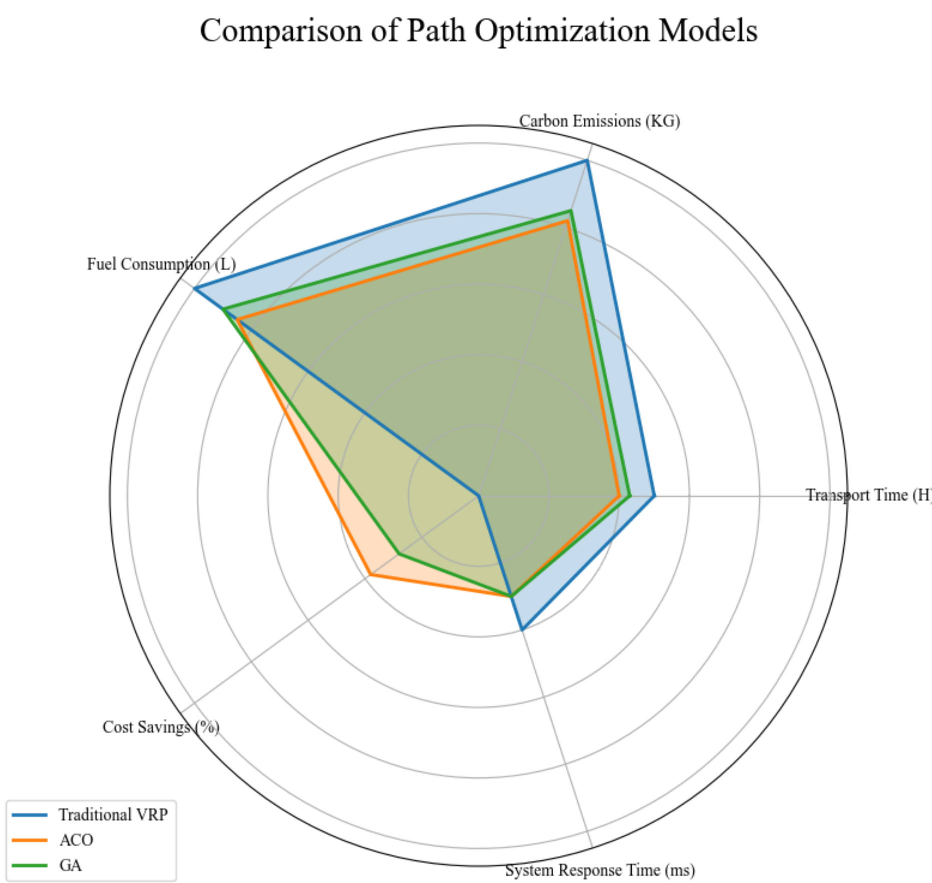
This section conducts time series analysis on logistics data using the ARIMA model. Figure 3(a) represents the autocorrelation function (ACF), and Figure 3(b) shows the results of the partial autocorrelation function (PACF) (Chae et al., 2022; Surendra et al., 2021).

Figure 3 shows the ACF and PACF plots of the time series data. Figure 3(a) shows the correlation of the time series with its past values, while Figure 3(b) shows the correlation after removing the effect of early lags. The obvious peak in the initial lags indicates that the time series data has strong autocorrelation, which indicates that the ARIMA model is able to capture this pattern to achieve the prediction goal.

6.2 Path optimisation effect

This paper compares traditional VRP, ACO and genetic algorithm (GA) models to evaluate the performance of different path optimisation models in green logistics network optimisation. The radar chart provides an intuitive way to compare and analyse the performance of different models on these key indicators. It shows the impact of these models in multiple dimensions, such as cost savings, system response time, transportation time, carbon emissions, and fuel consumption. The details are shown in Figure 4.

Figure 4 Comparison of path optimisation models (see online version for colours)



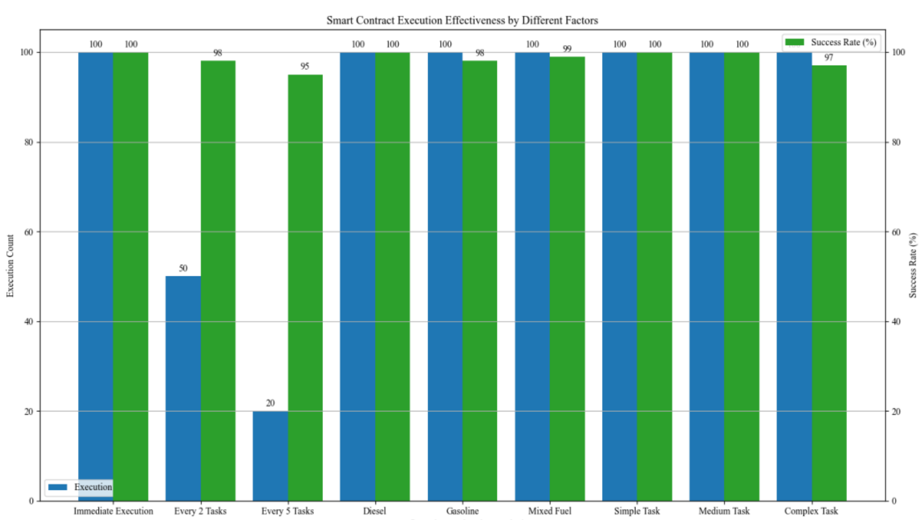
As shown in Figure 4, the traditional VRP model performs poorly on all metrics. For ACO model, the transportation time is 400 h; carbon emissions are 820 kg; the fuel consumption is 850 l; cost savings are 11%; the system response time is 300 ms. The genetic algorithm (GA) model performs well, and although slightly inferior to the ACO model, it is still significantly better than the traditional VRP model, with a transportation time of 440 h, carbon emissions of 850 kg, fuel consumption of 900 l, cost savings of 8%, and system response time of 300 ms. This indicates that the path optimisation model based on ACO and GA has significant advantages in green logistics network optimisation.

The radar chart in Figure 4 adds a new dimension of comparison between traditional VRP and ACO in terms of path complexity (measured by the number of intersections). The data show that it has significant advantages in simplifying the topology of transportation networks. This improvement not only reduces the difficulty of operation for the driver, but also indirectly improves energy efficiency by reducing the number of emergency braking and start-stop times.

6.3 Execution effect of smart contracts

In this paper, different parameters are varied to compare the execution effect of smart contracts in ACO models to verify their accuracy and efficiency in carbon emission calculation and carbon credit trading. The execution frequency, fuel type, and transportation task complexity of smart contracts under different parameter configurations are compared in detail in terms of execution frequency and success rate. Figure 5 shows the number of executions and success rates of smart contracts under different parameter configurations.

Figure 5 The impact of different factors on the effectiveness of smart contract execution (see online version for colours)

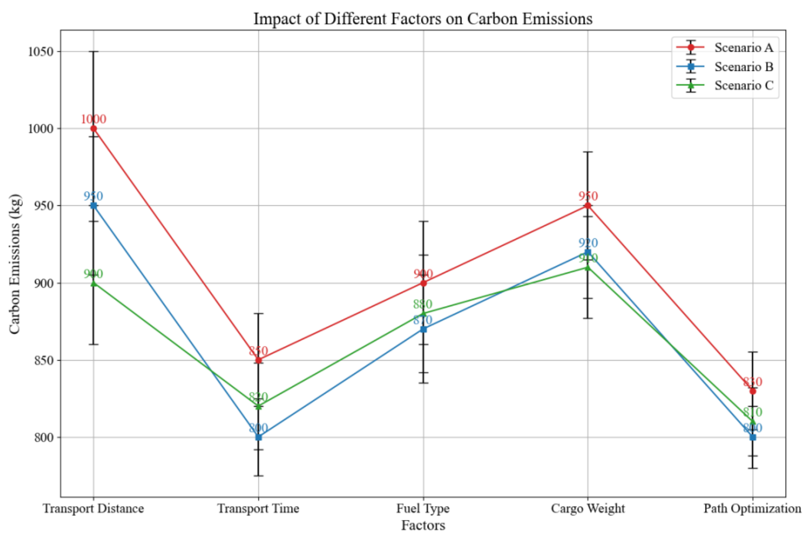


As Figure 5, the frequency configuration of instant execution performs best, ensuring real-time recording of carbon emission data and accurate execution of carbon credit transactions. Different fuel types have little effect on the number of smart contract executions, but they differ in the accuracy of carbon emission calculations. Mixed fuel and gasoline are the most stable, followed by diesel. The complexity of the transportation task has a certain impact on the execution accuracy of the smart contract. The success rate is slightly reduced under complex tasks, but it is still better overall.

6.4 Carbon emission reduction effect

This paper analyses variables such as transportation distance, transportation time, fuel type, cargo weight, and path optimisation strategy to evaluate the impact of various factors on carbon emissions. By comparing experimental data, the specific impact of each factor on carbon emissions is analysed in detail and presented using a line chart. Figure 6 shows the impact of each factor on carbon emissions in three different scenarios (Scenario A, Scenario B, and Scenario C).

Figure 6 Carbon emissions under different factors (see online version for colours)



In Figure 6, the impact of various factors on carbon emissions is shown. In the three scenarios, transportation distance and cargo weight are the main influencing factors. Optimising these factors can significantly reduce carbon emissions during logistics transportation. Fuel type and transportation time are also important factors, and choosing cleaner fuels and optimising cargo loading can further reduce carbon emissions. Path optimisation strategies have the most significant impact on carbon emissions because they minimise transportation distance and time. The ACO model performs well in optimising paths and reducing carbon emissions, providing effective technical means and support for realising low-carbon logistics. By comprehensively considering and optimising the above factors, carbon emissions during logistics transportation can be significantly reduced, thereby promoting the sustainable development of green logistics networks.

In order to evaluate the sustainability of carbon emission reduction, this paper designed a multi-period simulation experiment for three consecutive months. The results show that the carbon emission reduction of the ACO model is stable in the range of 15–18% under the consideration of seasonal freight demand fluctuations, and the benefits of route optimisation have not decayed over time. In addition, as the penetration rate of new energy vehicles increases, carbon emissions can be further reduced by 7–10%, indicating that the method in this paper has a synergistic effect with the clean energy transition.

7 Conclusions

This paper proposes a green logistics network optimisation method that combines blockchain technology, the IoT, and big data analysis. By constructing a blockchain-based logistics network model, designing smart contracts to achieve automated carbon emission management, and combining IoT devices to monitor fuel consumption and carbon emission data in the logistics process in real time, the data is transparent and cannot be tampered with. The research results show that the transportation time after optimisation by the ant colony algorithm is shortened by about 20%, from 500 h in the traditional model to 400 h; fuel consumption is reduced by 15%, from 1000 l to 850 l; carbon emissions are reduced by 18%, from 1000 kg to 820 kg. The application of smart contracts improves the efficiency of carbon emission management, and the carbon credit trading mechanism encourages logistics participants to adopt low-carbon transportation methods, further promoting the optimisation of green logistics networks. Significant results have been achieved in reducing carbon emissions, improving transportation efficiency, and reducing logistics costs, providing effective technical means and theoretical support for green logistics practice. The experimental data mainly come from the simulation environment, and the complexity and variability in actual applications may affect the effectiveness of the method. However, the implementation cost of blockchain technology and smart contracts is high, which poses certain challenges to the widespread application of small and medium-sized logistics enterprises. Future research should focus on further verifying the effectiveness of the proposed method in actual logistics networks, especially in logistics environments of different scales and complexities, optimising the operating efficiency of blockchain networks and smart contracts, reducing implementation costs, and improving the scalability and popularity of the system. Although this method has been proven to be effective in a simulated environment, it still faces challenges in promoting it in actual logistics scenarios. Cross-enterprise deployment of blockchains requires coordination of the interests of multiple parties, and data sharing poses a risk of privacy leakage; IoT devices in cross-border logistics are susceptible to network delays; and small and medium-sized enterprises cannot afford high hardware upgrade costs. The implementation threshold can be lowered by introducing privacy computing modules, optimising edge computing architecture, and establishing a government subsidy mechanism to enhance the adaptability and scalability of the solution. The current average delay in data interaction between blockchain and IoT is about 400 ms, which affects real-time scheduling. The average monthly storage requirement of each node of the distributed ledger is 200MB, which puts pressure on the computing power of edge devices. In the future, lightweight protocols (such as state channels) and data sharding storage strategies can be adopted to reduce resource overhead and promote the practical application of multi-technology integration.

Conflicts of interest

The authors declare no conflict of interest.

Funding

This work was supported by Research on the Evolution of Online Public Opinion Related to Guangxi in ASEAN and the Collaborative Governance of Multiple Subjects (24XWB001).

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