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Data-Driven and Sustainable Transportation Route Optimization in Green Logistics Supply Chain

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Abstract: In the green logistics supply chain, transportation route optimization faces urgent problems such as high energy consumption and environmental pollution. This paper aims to achieve sustainable optimization of transportation routes through a data-driven approach. First, a large amount of transportation-related data is collected, including vehicle operation information, cargo characteristics, road conditions and meteorological factors. Big data analysis technology is used to clean and extract features from the data, and a transportation demand forecasting model is constructed. Then, a new optimization model is designed using the particle swarm optimization algorithm, with the goal of minimizing transportation costs and carbon dioxide emissions. In actual application cases, by optimizing the transportation routes of a logistics company, the results showed that the lowest transportation cost was 1,512 dollars and the lowest carbon dioxide emissions were 1.2 tons. Data-driven transportation route optimization not only improves logistics efficiency, but also promotes environmental sustainable development.

Keywords: Green Logistics Supply Chain; Transportation Route Optimization; Data-Driven; Sustainable Development

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1. Introduction

In the context of the continued development of the global economy, the rapid growth of the logistics industry has brought significant energy consumption and environmental pollution problems. Traditional transportation methods often rely on high-energy fuels and inefficient transportation routes, which not only increases operating costs but also has a serious impact on the ecological environment. With the popularization of the concept of sustainable development, green logistics has gradually become an important direction for the development of the industry. Optimizing transportation routes to reduce energy consumption and emissions has become a core issue that needs to be solved urgently.

To meet this challenge, data-driven approaches have shown unique advantages in logistics optimization. By collecting and analyzing a large amount of transportation-related data, including vehicle operation information, cargo characteristics, road conditions and meteorological factors, logistics companies can more accurately predict transportation demand and conduct efficient route planning based on this. The use of advanced algorithms, such as particle swarm optimization (PSO), can minimize environmental impact while ensuring economic benefits, thereby promoting the logistics industry to develop in a green and sustainable direction.

This paper is organized as follows: the second part reviews the relevant literature in detail and explains the current research progress and shortcomings in the field of green logistics; the third part introduces the methods of data collection and processing, including data cleaning and feature extraction processes; the fourth part focuses on the construction of the transportation demand forecasting model and its algorithm implementation; the fifth part shows the actual application case, analyzes the optimization results and their contribution to logistics efficiency and environmental impact; finally, the sixth part summarizes the research results and proposes the direction and prospect of future research. Through such a structure, this paper aims to provide practical theoretical support and practical guidance for the optimization of green logistics supply chain.

2. Related Work

With the increasing awareness of environmental protection and the advancement of technology, optimizing logistics transportation routes has become a hot topic in research. Sun [1] studied the optimal ship transportation route planning method based on swarm intelligence optimization algorithm to avoid potential static obstacle risk areas in the marine transportation environment, perform smooth and dynamic obstacle avoidance, and reduce the risk of ship collision. Liu et al. [2] analyzed the energy consumption problem of open-pit mine truck transportation from the perspective of carbon emissions, set carbon emission costs and transportation costs as optimization targets, and fully considered various transportation routes and work tasks from different loading points to different unloading points, and constructed an open-pit mine oil-electric mixed truck transportation optimization model under low-carbon constraints. Zhang and Han [[3] described the current status of China's rice supply chain production, processing, warehousing, sales, and consumption. On the basis of following the rice supply chain optimization principles such as overall optimization, demand orientation, informatization, collaborative cooperation, and sustainable development, they fully considered each link and explored its design and implementation from the perspective of the rice supply chain system in order to propose targeted solutions. Liu [4] explored how to deeply optimize the supply chain of fresh agricultural products in the context of digitalization through effective information management, advanced logistics technology, and intelligent decision-making systems to adapt to today's complex and changing market environment. In order to optimize the overall supply chain goals, Yu et al. [5] used supply chain optimization software to build a supply chain optimization model that covers demand, procurement, production, storage, transportation and other links. Putha[6] explored the application of AI-driven predictive analysis in supply chain optimization in the automotive industry, focusing on improving demand forecasting, inventory management, and logistics efficiency. Sahu[7] explored the impact of AI on supply chain resilience and flexibility, considering how AI systems can adapt to disruptions and changes in the supply chain environment. The study by Baloch and Rashid [8] helps to assess many important issues, research trends, and breakthroughs in the supply chain management industry. Ikevuje et al. [9] explored the transformative impact of the Internet of Things and data analytics on supply chain operations, emphasizing their role in increasing efficiency, reducing costs, and improving performance. Reddy and Nalla [10] explored the transformative potential of predictive big data analytics in optimizing e-commerce supply chains. By leveraging advanced analysis, e-commerce companies can enhance decision-making processes related to inventory management, demand forecasting, and logistics operations. Various studies have shown that advanced technologies have significant potential to improve supply chain efficiency and sustainability.

3. Methods

3.1 Data Collection

This paper first identifies the key data types that need to be collected, including vehicle operation information, cargo characteristics, road conditions, and meteorological factors. These data will help build efficient transportation demand forecasting models and optimization algorithms. Vehicle operation information is mainly collected through the vehicle GPS system and logistics management software. The data includes vehicle ID, mileage, fuel consumption, transportation time, and driving behavior [11]. This information can help evaluate the operating efficiency of vehicles and understand the energy consumption of different transportation tasks. In terms of cargo characteristics, this paper focuses on the weight, volume, type and special requirements of cargo (temperature control, fragility, etc.), which directly affect the loading method and route selection of transportation. Traffic data is obtained through traffic monitoring systems and various real-time traffic applications, covering road types (highways, urban roads), traffic flow, and road condition information (construction, accidents, etc.). This data is essential for evaluating transportation time and determining the best driving route. At the same time, meteorological factors are collected using local weather stations and online weather services to obtain information such as temperature, precipitation, wind speed, etc. These factors may affect safety and efficiency during transportation. Table 1 shows some sample data collected:

Table 1: Some sample data collected

Data Type	Vehicle ID	Distance Traveled (km)	Fuel Consumption (L)	Cargo Weight (kg)	Road Condition	Temperature (°C)	Traffic Flow (vehicles/h)
Vehicle Data	A001	120	15	800	Highway	25	200
Vehicle Data	A002	80	10	500	City Road	30	300
Cargo Features	A003	150	20	1000	Highway	22	150
Road Condition	A004	90	12	600	Construction Zone	28	100
Weather Factors	A005	110	18	750	Highway	20	250

3.2 Feature Extraction and Processing

This paper first cleans the collected data to eliminate noise and inconsistency. Data cleaning includes processing missing values, removing outliers, and standardizing data. Missing value processing uses mean filling and interpolation methods to ensure data integrity. For example, if the fuel consumption data of a vehicle is missing, it can be filled with the average fuel consumption of the vehicle's other trips. The Z-score method is used to detect outliers. Outliers are defined as data points with an absolute value of Z-score greater than 3, and are removed to ensure data accuracy [12]. Next, feature extraction is performed. Features closely related to transportation efficiency and environmental impact are extracted from the raw data, such as vehicle fuel efficiency, carbon dioxide emissions per unit of cargo, etc. Fuel efficiency can be calculated using the following formula:

$$\text{Fuel Efficiency} = \frac{\text{Distance Traveled (km)}}{\text{Fuel Consumption(L)}} \tag{1}$$

This paper also constructs a load factor feature, which represents the ratio of the actual cargo load of each vehicle to its maximum cargo load capacity. The calculation formula is:

$$\text{Load Factor} = \frac{\text{Cargo Weight (kg)}}{\text{Maximum Load Capacity(kg)}} \tag{2}$$

When dealing with road conditions and weather factors, we encode non-numeric data and use One-Hot Encoding to convert road condition types into numerical features. The meteorological data was standardized to a range of 0 to 1 to eliminate its impact on model training. Through this series of data cleaning and feature extraction, we constructed a more refined and effective feature set.

3.3 Construction of Transportation Demand Forecasting Model

This paper uses a method combining time series analysis and machine learning to construct a transportation demand forecasting model to improve the accuracy and reliability of the forecast[13]. First, data preprocessing is performed based on the collected historical transportation data, including transportation volume, road conditions, meteorological factors, etc., to ensure the continuity and consistency of the data. Considering the time series characteristics of the data, we try the autoregressive integrated moving average (ARIMA) model, which is suitable for processing linear time series data. The data was tested for stationarity, the ADF (Augmented Dickey-Fuller) test was used to determine the stationarity of the time series, and difference processing was performed to eliminate trends and seasonality. The parameters (p, d, q) of the ARIMA model were optimized using the grid search method to ensure the best fit of the model. On this basis, the long short-term memory (LSTM) network is introduced as an effective time series forecasting method for deep learning. LSTM can handle long-term dependency problems and is suitable for capturing complex patterns of transportation demand. The input of the model is the data of the previous n time steps, and the output is the transportation demand of the next time step [14]. To evaluate the performance of the model, the root mean square error (RMSE) is used as the evaluation indicator. The specific calculation method is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \tag{3}$$

By comparing the prediction results of ARIMA and LSTM models, we find that LSTM performs better in capturing the volatility of transportation demand.

3.4 Design of Particle Swarm Optimization Algorithm

In transportation route optimization, the core of this paper is the application of particle swarm optimization (PSO), where modeling is determined parameters to minimize transportation costs and CO_2 emissions. The collaborative work of the particle swarm iteratively updates the position and velocity of each particle until the optimal solution is reached. First, in an objective function that comprehensively considers transportation costs and carbon dioxide emissions, the transportation cost is set as C and the carbon dioxide emissions are set as E. The objective function can be expressed as:

$$F(x) = w1 * C + w2 * E \tag{4}$$

w1 and w2 are the weight coefficients of transportation cost and carbon dioxide emission, respectively, and w1+w2=1. By adjusting these two weights, the target can be flexibly optimized according to actual needs. In each iteration, the particle adjusts its speed and position according to its own historical optimal solution and the global optimal solution. The position of the particle represents the choice of transportation route, which is based on the actual road network and constraints[15] to ensure that the transportation route represented by each particle is feasible. During the optimization process, constraints include transportation time, vehicle load limit, and environmental regulations. Through iterative updates, particles continuously explore the solution space and eventually converge to the optimal solution. After multiple iterations, the PSO algorithm can effectively find the best transportation route that minimizes transportation costs and carbon dioxide emissions, providing a scientific basis and decision support for green logistics.

4. Results and Discussion

4.1 Selection of Practical Application Cases

In this paper, an actual transportation case of a medium-sized logistics company was selected as the application object to verify the effectiveness of the proposed transportation demand prediction model and particle swarm optimization algorithm. The company is mainly responsible for the distribution of goods between cities and faces the dual challenges of high transportation costs and environmental impact, so the selection of this case has important practical significance. The logistics company involves multiple transportation routes in its daily operations, and the transportation volume, road conditions and weather conditions of each route are different. We collected the company' s transportation data over the past year, including cargo type, weight, transportation time, fuel consumption, and CO_2 emissions for each route. This data provided a solid foundation for model construction.

When selecting specific transportation cases, we focused on routes with high frequency transportation to ensure that the optimized results could significantly impact overall operational efficiency. After analysis, we selected 12 major inter-city transport routes, all of which connect two important logistics hubs, have large daily transport volumes, and have obvious transport cost and environmental impact issues. By predicting the transportation demand for this route and optimizing the route using a particle swarm optimization algorithm, we expect to reduce carbon dioxide emissions while lowering transportation costs.

4.2 Description of the Optimization Process

In the actual application case, the optimization process is divided into several key steps. First, the transportation demand forecasting model constructed earlier is used to forecast the future demand of the target transportation route and obtain the expected cargo transportation volume and distribution. This step ensures that we can make decisions based on accurate demand data during optimization. Next, based on the prediction results, the PSO algorithm optimizes the transportation route and initializes a group of particles, each of which represents a possible transportation route. Then, the objective function value is calculated based on the transportation cost and carbon dioxide emissions of each route. By iteratively updating the speed and position of each particle, the particle continuously searches for the optimal solution in the solution space.

In each iteration, particles adjust their behaviors according to their respective historical best positions and the global best position of all particles to optimize path selection and determine stopping conditions, such as reaching the maximum number of iterations or satisfying the convergence of the objective function to a certain threshold. During the optimization process, constraints such as vehicle load limits and transport time limits are taken into account to ensure that the generated routes are achievable in practice.

4.3 Result Analysis

In the actual test, the genetic algorithm (GA) was selected as the comparison algorithm to optimize the transportation route, and the transportation time, transportation cost and carbon dioxide emissions were used as evaluation indicators. The 12 routes selected above were used as test routes. Figure 1 shows the transportation time test results, and Figure 2 shows the transportation cost results:

Figure 1: Shipping time

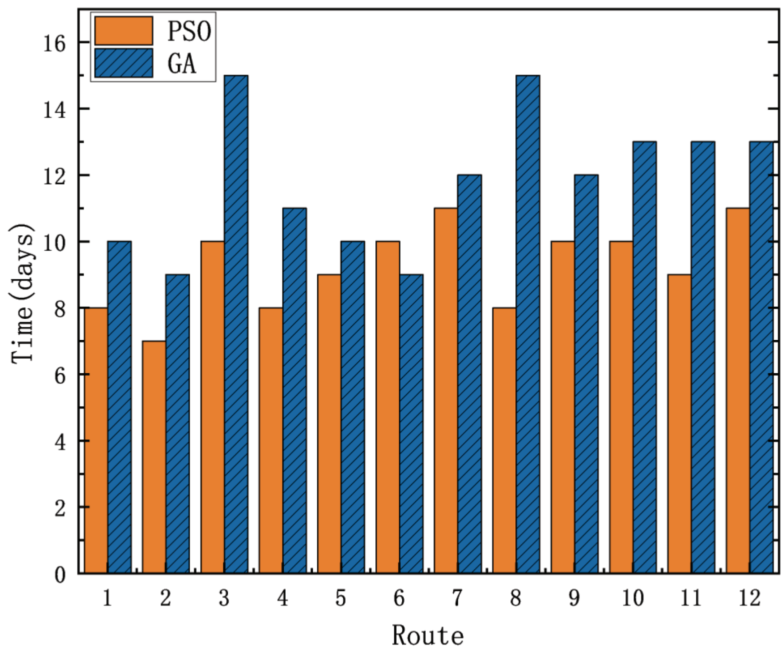
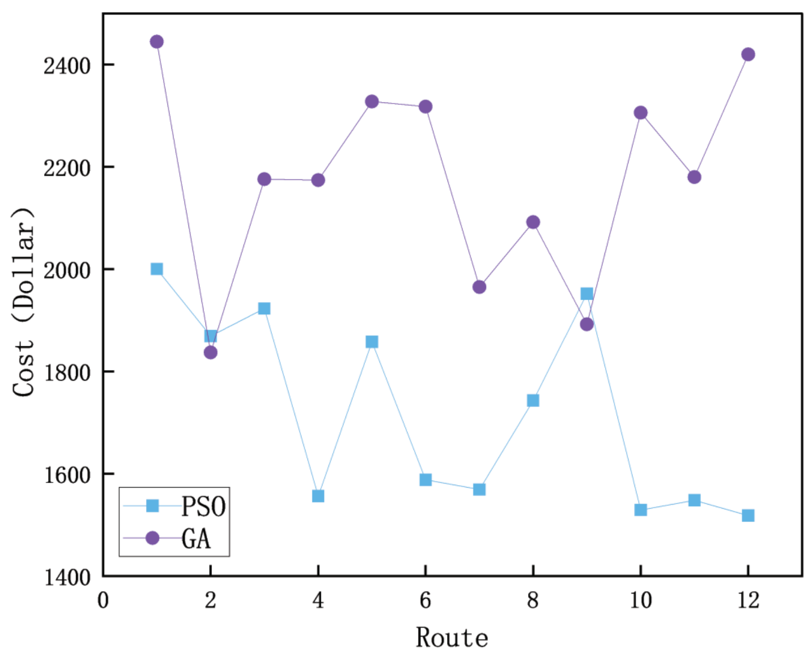


Figure 2: Transportation costs



In the actual test, the PSO algorithm and GA are fully applied and compared for 12 transportation routes. It is observed that PSO is significantly better than GA in terms of transportation time and transportation cost. Moreover, the transportation time of PSO is shorter than that of GA overall, with only route 6 being slightly better, with the maximum difference of 7 days. This trend may stem from the fact that the PSO algorithm is more flexible when dealing with multi-dimensional search spaces and can better adapt to changes in transportation needs, thereby optimizing route selection. Regarding transportation costs, PSO also performs well. The cost of multiple routes is significantly lower than GA. Especially on route 12, PSO saves nearly 700 dollars, with the lowest cost being 1,512 dollars. This shows that PSO can more effectively integrate transportation resources and route planning and reduce overall operating costs. GA shows higher transportation costs in some cases, which may be affected by the diversity of solutions brought by its crossover and mutation operations, resulting in wandering in the local optimal solution and failing to find a more cost-effective route optimization solution. The trend of these data changes clearly shows that the PSO algorithm has more advantages in optimizing the efficiency and economy of transportation routes, and provides more effective tools and methods for the implementation of green logistics. Figure 3 is a comparison of carbon dioxide emissions:

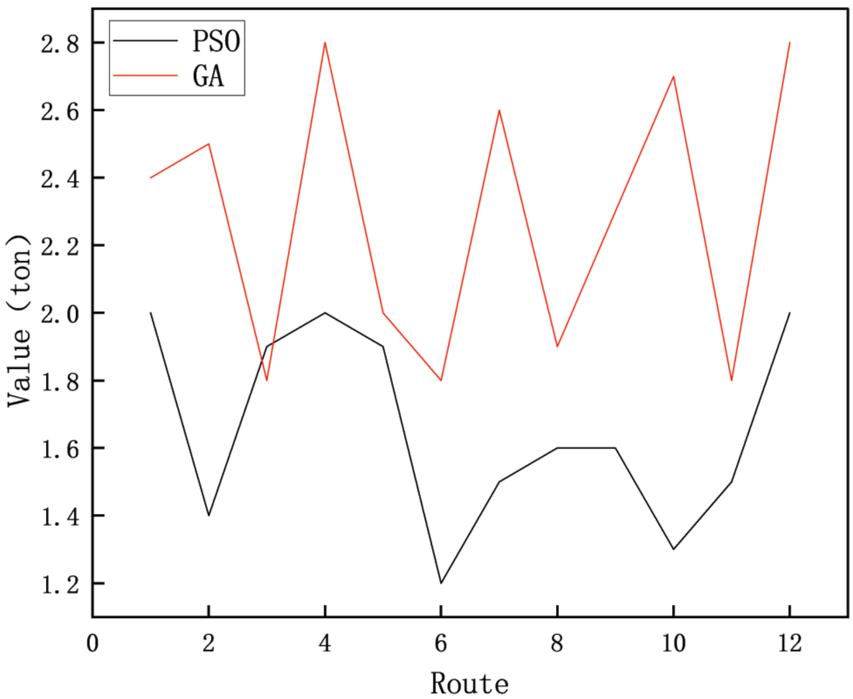


Figure 3: Carbon emissions

In the results of testing carbon emissions (tons), the particle swarm optimization (PSO) algorithm shows obvious advantages on most paths, demonstrating its effectiveness in reducing carbon dioxide emissions. Specifically, the carbon emissions of PSO are generally lower than those of genetic algorithm (GA). For example, on route 2 and route 6, PSO saves 1.1 tons and 0.6 tons of carbon dioxide emissions, respectively. This trend may be due to the fact that the PSO algorithm better integrates transportation demand, vehicle efficiency, and road condition information in the route selection process, thereby achieving a more optimal resource allocation. Relatively speaking, GA exhibits higher emissions on some routes, especially on routes 4 and 12, with emissions of 2.8 tons each, indicating that it may fall into the limitation of local optimal solutions when finding the best route, which leads to higher carbon emissions. Overall, PSO not only reduces transportation time and costs during the optimization process, but also effectively reduces carbon emissions, which provides scientific basis and practical support for the implementation of green logistics. Such data trends reflect the significant differences in the environmental impact of different optimization algorithms, emphasizing the importance of selecting appropriate optimization tools in logistics management.

5.Conclusion

Through a data-driven approach, this paper successfully constructed a transportation route optimization model based on LSTM and particle swarm optimization PSO algorithm, which significantly improved the transportation efficiency and sustainability of the green logistics supply chain. Empirical results show that compared with traditional genetic algorithms, PSO has more significant advantages in reducing transportation time, cost and carbon dioxide emissions. This research not only provides practical decision support for logistics companies, but also lays a theoretical foundation for the development of green logistics. However, the dataset used in this paper is relatively small, which may affect the generalization ability of the model. Future research directions can focus on expanding the scale and diversity of the dataset to improve the robustness of the model. At the same time, combined with real-time data monitoring and dynamic optimization technology, the adaptability of the model in complex environments can be further improved.

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