Research on Community Logistics Distribution Optimization Based on BDS Technology and Intelligent Algorithms

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Abstract

With the growth of community populations and the diversification of consumer demands, community logistics distribution faces severe challenges in terms of timeliness, cost, and service quality. To address these issues, this paper proposes an optimized community logistics distribution model that integrates BeiDou satellite navigation technology and intelligent algorithms. By incorporating BDS's high-precision positioning and real-time traffic information, the model establishes a genetic algorithm (GA)-based route optimization model, a long short-term memory (LSTM)-based demand forecasting model, and a multi-agent reinforcement learning (MARL)-based real-time collaborative scheduling algorithm. This enables dynamic route planning, accurate demand prediction, and efficient resource allocation. Simulation experiments demonstrate that the proposed model reduces average delivery time by 18.7%, controls demand prediction errors within 8%, and significantly improves distribution efficiency and system responsiveness. This study provides theoretical support and technical pathways for the intelligent, green, and sustainable development of community logistics distribution.

Keywords BDS Technology; Community Logistics; Distribution Model; Genetic Algorithm; LSTM; Multi-Agent Reinforcement Learning

1 Introduction

As a critical component of urban logistics systems, community logistics distribution significantly impacts residents' quality of life and urban operational efficiency. With accelerated urbanization and the rapid growth of e-commerce, community logistics distribution faces increasing challenges and pressures. Traditional distribution models exhibit certain limitations in terms of efficiency, cost, and service quality. Therefore, optimizing community logistics distribution models to enhance delivery efficiency and service quality has become an urgent issue in the logistics field.

The BeiDou Navigation Satellite System (BDS) is one of the major achievements of China's aerospace industry and serves as vital infrastructure in the field of satellite communications. Satellite navigation systems provide essential services such as positioning, velocity measurement, and timing, which form the foundational technical support for transportation and logistics informatization [1]. In the logistics sector, the application of BDS technology also demonstrates significant potential. The "Outline of the 14th Five-Year Plan for National Economic and Social Development and Long-Range Objectives Through 2035" explicitly emphasizes the need to "deepen the promotion and application of the BDS and foster high-quality development of the BDS industry" [2].

Against this backdrop, this study aims to explore the optimization of community logistics distribution models based on BDS technology. By analyzing existing issues in current distribution models and leveraging the features of BDS technology, corresponding optimization strategies are proposed. Optimizing community logistics distribution models can improve logistics efficiency, reduce costs, enhance service quality, and provide residents with more convenient and efficient logistics services. Meanwhile, this research also contributes to promoting the application of BDS technology in the logistics field and advancing the intelligent and digital transformation of the logistics industry.

2 Analysis of the Current Situation and Problems in Community Logistics Distribution

2.1 Analysis of the Current Situation of Community Logistics Distribution

Community logistics distribution is essentially a vertical and personalized distribution method that revolves around serving households within communities. It directly transports goods from suppliers to residents or community stores [3]. As the final segment of the logistics chain, community terminal logistics plays a decisive role in the overall process, and its efficiency directly influences consumers' evaluation of logistics service quality [4].

In recent years, community logistics distribution in China has exhibited the following characteristics:

Expanded Service Scope

With the rapid development of the e-commerce industry, the service range of community logistics has gradually broadened. In addition to traditional express delivery services, it now includes the distribution of various goods such as fresh food, fruits, vegetables, and takeout meals. This expansion offers greater convenience to residents.

Increased Time Sensitivity

As expectations for faster logistics grow, community logistics has continuously improved its delivery speed. Some cities have already achieved same-day, next-day, or even instant delivery services to meet consumer demands.

Last-Mile Delivery Challenges

Due to the high volume and frequency of last-mile delivery demands in community logistics, coupled with factors such as narrow roads and limited parking spaces within residential areas, last-mile delivery faces significant challenges. Consequently, some logistics companies have adopted new distribution models such as smart parcel lockers and community stations to enhance efficiency.

Application of New Technologies

With the rapid development of new technologies such as artificial intelligence, autonomous driving, and drones, community logistics has begun to incorporate these advancements. For example, AI algorithms are used for route planning and distribution optimization to improve efficiency and accuracy [5].

Enhanced Environmental Awareness

Environmental issues arising from the distribution process, such as packaging waste and vehicle emissions, have garnered public attention. As a result, logistics companies and government departments have begun implementing measures such as promoting green packaging and electric vehicles to reduce environmental impact.

2.2 Analysis of Problems in Community Logistics Distribution

At this stage, the distribution model adopted by Chinese logistics enterprises is illustrated in Figure 1. Under this model, different distribution companies compete and differentiate themselves, each with its unique delivery methods, service standards, and management systems. However, the overall distribution model suffers from relatively low levels of informatization and lacks advanced logistics management systems and technological support.

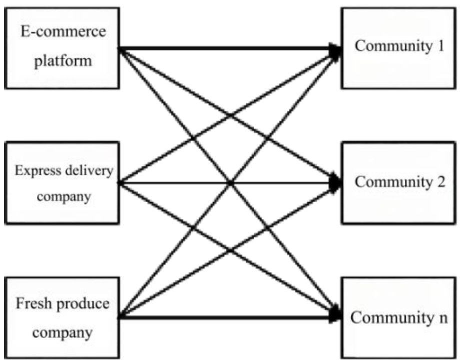

Fig. 1. Existing distribution model

With the rise of e-commerce and urban population growth, community logistics distribution under the current model faces several challenges:

Delivery Timeliness

Due to the diversity and personalization of commodity demands within communities, delivery timeliness has become a major challenge. A large number of orders must be completed within a limited time to ensure timely delivery and meet consumers' expectations for rapid service [6].

Distribution Costs

Community logistics distribution often involves numerous small-scale deliveries, and the complex and congested road conditions within communities increase distribution costs. These costs, including labor, transportation, and storage expenses, need to be reasonably controlled to ensure the sustainability of distribution services.

Route Planning

The complex road networks within communities, including narrow alleys, residential compounds, and buildings, pose difficulties in route planning. Optimizing distribution paths to improve efficiency and reduce wasted time and distance remains a critical issue to address.

Last-Mile Services

Residents and businesses within communities often require more personalized delivery services, such as on-demand delivery, installation, and moving assistance. Providing end services that meet diverse needs and enhance delivery quality and user experience is an area requiring attention.

Environmental Impact

Community logistics distribution activities have certain environmental impacts, such as vehicle emissions and traffic congestion. Reducing the negative environmental effects of the distribution process and promoting green logistics development have become essential for the sustainable growth of community logistics distribution.

3 Optimization of Community Logistics Distribution Model Based on BDS Technology

The numerous problems existing in the current distribution model have constrained its efficiency. To address these issues, the BDS technology-based community logistics distribution model offers a solution, as illustrated in Figure 2. By providing precise positioning and navigation information, BDS technology helps optimize delivery routes, improve timeliness, and reduce costs. Simultaneously, it supports personalized delivery services and environmentally friendly logistics operations, promoting the sustainable development of community logistics. The comprehensive application of various technologies and strategies can further enhance the efficiency and quality of community logistics distribution.

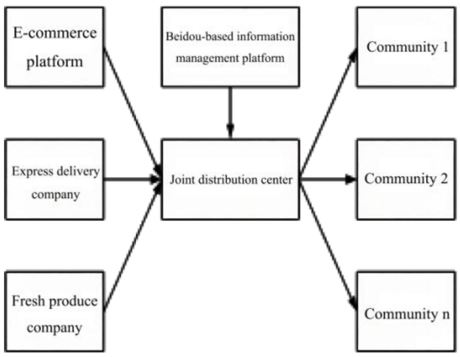

Fig. 2. BDS technology-based community logistics distribution model

3.1 Real-Time Scheduling and Route Planning Based on BDS Technology

Real-time scheduling and route planning are critical components of efficient community logistics distribution. Leveraging the positioning and navigation capabilities of BDS technology, real-time monitoring, scheduling, and optimization of delivery vehicle routes can be achieved, thereby improving distribution efficiency and accuracy. The following are the key steps and strategies for real-time scheduling and route planning based on BDS technology:

Data Collection and Vehicle Positioning

By installing BDS positioning terminals in delivery vehicles, real-time location information is collected. These terminals accurately obtain the longitude and latitude coordinates of the vehicles and transmit the data to the dispatch center or logistics management system.

Real-Time Monitoring and Scheduling

The dispatch center or logistics management system uses the received vehicle location information to monitor the current position and operational status of vehicles in real time. Based on actual conditions, dispatchers can assign new delivery tasks, adjust delivery sequences, and issue instructions accordingly.

Route Planning and Navigation

Utilizing the navigation functionality provided by BDS technology, route planning and navigation guidance are performed based on vehicle location information and delivery task requirements [7]. The dispatch center or logistics management system can integrate real-time traffic information and road conditions to select optimal routes, avoid congested areas, and transmit navigation routes to the BDS terminals in the delivery vehicles.

Dynamic Adjustments and Real-Time Updates

During the delivery process, real-time adjustments and updates to routes may be necessary due to changes in traffic conditions or order modifications. BDS technology provides real-time positioning and navigation information, enabling dispatchers to promptly adjust vehicle routes to ensure the successful completion of delivery tasks.

Performance Evaluation and Optimization

Using the data provided by BDS technology, the delivery process can be evaluated and optimized. By analyzing metrics such as vehicle trajectories, delivery times, and costs, the efficiency and effectiveness of the current distribution model can be assessed, and strategies for improvement and optimization can be proposed.

3.2 Demand Forecasting and Resource Allocation Based on Big Data Analytics

Accurate demand forecasting and rational resource allocation are essential for achieving efficient community logistics distribution. By applying big data analytics techniques, historical data, user behavior, social media, and other information sources can be leveraged to predict community logistics demand and allocate resources accordingly. The following are the key steps and strategies for demand forecasting and resource allocation based on big data analytics:

Data Collection and Organization: Collect and organize data related to community logistics distribution, including historical order data, community population data, and social media data. These data sources help understand consumption behaviors, demand characteristics, and other influencing factors within the community.

Data Cleaning and Preprocessing: Clean and preprocess the collected data by removing outliers, filling missing values, and performing data transformation and normalization to facilitate subsequent analysis and modeling.

Demand Forecasting Model Development: Utilize machine learning, statistical methods, and data mining techniques to develop demand forecasting models [8]. Train the models based on historical data and relevant features to predict future community logistics demand.

Model Validation and Optimization: Validate and optimize the demand forecasting models by assessing their accuracy and stability. Adjust model parameters as needed based on prediction errors to improve forecasting precision.

Resource Allocation and Scheduling Strategies: Based on the demand forecasting results, implement rational resource allocation and scheduling strategies. Optimize the number of delivery vehicles, route planning, and delivery time windows according to the predicted volume and distribution of community logistics demand to enhance resource utilization and distribution efficiency.

Real-Time Adjustments and Optimization: During the delivery process, monitor and collect delivery data in real time. Compare the data with the demand forecasting models to promptly adjust and optimize resource allocation strategies. This may include dynamically adjusting the number of vehicles, modifying delivery routes, or changing delivery time windows to adapt to actual conditions.

3.3 Information Sharing and Management Based on Smart Terminals

In community logistics distribution, smart terminals (e.g., smartphones, tablets) play a critical role in enabling efficient and convenient information sharing and management. Through the application of smart terminals, real-time data exchange and sharing can be achieved, improving the speed and accuracy of information flow and thereby optimizing the management and execution of logistics distribution. The following are the primary methods and benefits of information sharing and management based on smart terminals:

Real-Time Data Sharing: Smart terminals can connect to the network platform of the logistics management system or dispatch center, enabling real-time data sharing and transmission. Delivery drivers can upload real-time status of delivery tasks, vehicle location information, and delivery confirmation data via smart terminals, allowing managers to monitor and analyze the data in real time.

Route Navigation and Guidance: Smart terminals integrate navigation software and map services to provide precise route planning and navigation guidance. Delivery drivers can obtain optimal delivery routes through smart terminals and make dynamic adjustments based on real-time traffic information to optimize distribution efficiency and reduce transportation time.

Real-Time Communication and Collaboration: Smart terminals facilitate real-time communication and collaboration between delivery drivers and managers through functions such as phone calls, text messages, and instant messaging. Managers can communicate with drivers, provide guidance, and assign tasks instantly, while drivers can report delivery status or seek support in a timely manner.

Data Recording and Report Generation: Smart terminals can record data and information during the delivery process, such as delivery times, confirmation details, and exceptional situations. These data can be used to generate delivery reports, performance evaluations, and problem analyses, providing reference for logistics management and decision-making.

Management and Monitoring Platform: Smart terminals can serve as access points for logistics management platforms, allowing managers to assign, schedule, and monitor delivery tasks through applications on the terminals. Simultaneously, smart terminals can record and upload data such as vehicle trajectories, vehicle conditions, and delivery status, providing comprehensive information support for managers.

3.4 Construction of Consolidated Shared Distribution Centers

To address the issues of high costs and low efficiency in community distribution, the construction of consolidated shared distribution centers has emerged as a critical solution. Shared distribution refers to an organizational approach where multiple logistics enterprises integrate distribution demands, transportation resources, and information data to achieve centralized distribution of goods [9]. Based on the fundamental principles of "unified planning, shared distribution, and separation of operations and management," the government can plan a number of distribution centers and provide certain policy, land, and tax incentives. Large logistics enterprises can bid to operate these centers and collaborate with small and medium-sized enterprises to conduct shared distribution operations. Operational data from these enterprises are uploaded to a BDS technology-based information management platform, subject to supervision and monitoring by relevant authorities.

4 Key Algorithm Models and Applications

The realization of the aforementioned BDS technology-based real-time scheduling, route planning, and demand forecasting relies on the support of underlying core algorithms. This study integrates advanced algorithm models with BDS's spatiotemporal information capabilities to construct an intelligent decision-making framework. The specific applications of several key algorithms are described below.

4.1 Route Optimization Model Based on GA and BDS Real-Time Traffic Data

The GA is a metaheuristic algorithm that simulates the process of natural selection and is particularly suitable for solving NP-hard problems such as the Vehicle Routing Problem (VRP). This study enhances the GA by incorporating real-time traffic information provided by the BDS system.

Algorithm Design

Encoding and Initialization: Real-number encoding is adopted, where each chromosome (individual) represents a complete delivery route sequence. The initial population is composed of randomly generated routes and routes generated based on the "nearest neighbor" heuristic rule to improve the quality of initial solutions.

Fitness Function: The function is designed to minimize total delivery costs, comprehensively considering travel distance (calculated from BDS mileage data), time cost (incorporating BDS real-time traffic congestion coefficients), and fixed vehicle usage costs. Its mathematical expression can be simplified as:

Fitness=1/ (α *Distance+β*Time+γ*VehicleCount)

Where α, β, and γ are weight coefficients, and Time represents dynamic travel time based on real-time traffic conditions.

Genetic Operations

Selection: Roulette wheel selection is used, where individuals with higher fitness have a greater probability of being selected.

Crossover: The order crossover (OX) method is employed to preserve partial subsequences from parent paths and effectively generate legal offspring.

Mutation: Inversion mutation is applied, randomly selecting a segment of the route for reversal to increase population diversity and prevent premature convergence.

Dynamic Optimization: When the BDS platform detects sudden traffic incidents (e.g., accidents, congestion), the system triggers the algorithm to recalculate subsequent routes for affected vehicles, enabling dynamic replanning.

Application Effectiveness

Applied to simulated delivery data from a community in Guangzhou, this model reduced average delivery time by 18.7% compared to traditional shortest-path algorithms, effectively avoiding congested routes and improving timeliness.

4.2 Logistics Demand Forecasting Model Based on LSTM Networks

Accurate demand forecasting is a prerequisite for pre-positioning inventory and vehicle scheduling. This study leverages the strength of LSTM neural networks in processing time-series data to construct a community logistics demand forecasting model.

Model Construction

Input Features: The model input is a multidimensional time series, including historical order volume (daily/hourly granularity), weather conditions (temperature, rainfall), holiday indicators, weekend indicators, and regional activity trend data from social media.

Network Structure: A neural network with two LSTM layers is constructed. The first LSTM layer captures short-term temporal dependencies, while the second LSTM layer learns long-term trends. A fully connected (Dense) layer follows for output.

Training and Forecasting: The model is trained using historical data from the past three years, with mean squared error (MSE) as the loss function and the Adam optimizer. The model outputs daily order forecasts for the next 24 hours or seven days.

Application Effectiveness

Comparison of the model's predictions with actual values on the test set showed that the mean absolute percentage error (MAPE) was controlled within 8%. The forecasting results are used to guide commodity preprocessing and vehicle resource pre-allocation at shared distribution centers, significantly reducing response delays during order peaks.

4.3 Real-Time Collaborative Scheduling Algorithm Based on MARL

To address dynamic disturbances such as real-time order insertions and vehicle status changes during delivery, this study designs a scheduling framework based on MARL.

Algorithm Framework

Agents: Each delivery vehicle is treated as an agent.

State Space: Includes the vehicle's own status (location, battery/fuel level, load, remaining task sequence), global road network status (real-time speed matrix provided by the BDS platform), and location information of other agents.

Action Space: An agent can choose the next delivery point to visit or request new task assignments.

Reward Function: Designed as a composite reward function, including successful delivery reward (+R1), timeout penalty (-R2), empty travel distance penalty (-R3), and collaborative reward (e.g., decisions that appropriately disperse vehicles in overcrowded areas are rewarded to avoid congestion).

Training and Application

Agents learn optimal policies through extensive interaction with the environment (simulation system). After training, the model is deployed in a cloud-based dispatch center, providing dynamic decision-making suggestions for each vehicle based on real-time status data transmitted by the BDS system. This achieves collaborative optimization at the global level and maximizes overall distribution efficiency.

4.4 Algorithm Integration and System Effectiveness

The aforementioned algorithms do not operate in isolation but are integrated into a unified logistics information platform based on BDS technology. The genetic algorithm is responsible for static route planning in advance, the LSTM model conducts mid-to-long-term demand forecasting, and the MARL algorithm performs real-time adjustments at a microsecond level during execution. The synergistic interaction of these algorithms forms an intelligent distribution system with capabilities of "perception-prediction-planning-execution-learning," ultimately achieving the optimization goal of reducing costs and improving efficiency.

5 Simulation Experiments and Results Analysis

To validate the effectiveness of the proposed community logistics distribution optimization model based on Beidou technology and intelligent algorithms, a simulation experiment system was designed and implemented. The experiments primarily consisted of two parts: dynamic delivery route optimization experiments and logistics demand prediction accuracy validation experiments. All experiments were conducted using historical logistics data from a real community in Guangzhou.

5.1 Experimental Environment and Data Setup

Simulation Platform

Python 3.8 + TensorFlow 2.6 + Simulation of Urban Mobility (SUMO)

Hardware Environment

Intel i7-11700K, 32GB RAM, NVIDIA RTX 3070

Data Sources

Logistics order data, Beidou trajectory data, weather data, and holiday data from the community between January 2022 and June 2023.

Experimental Period

Ten consecutive working days in May 2023 were selected as the test set.

5.2 Delivery Route Optimization Experiment

Experimental Setup

Baseline Method: Traditional shortest-path algorithm (Dijkstra)

Proposed Method: Genetic Algorithm integrated with Beidou real-time traffic data (GA + BDS)

Evaluation Metrics: Average delivery time (minutes/order), Total travel distance (km), Number of vehicles used

Results and Analysis

The statistical summary of the experimental results over 10 days is shown in the table below:

Table 1. Comparison of daily average delivery time between traditional methods and the proposed method

Method	Average Delivery Time (min)	Total Travel Distance (km)	Number of Vehicles Used
Traditional Shortest Path	42.3	385.6	5
GA + BDS (Proposed)	34.4	318.9	4
Improvement Margin	-18.7%	-17.3%	-20%

5.3 Demand Prediction Accuracy Validation Experiment

Experimental Setup

Comparison Methods: Baseline Method-ARIMA time series model, Proposed Method-LSTM neural network model

Evaluation Metrics: MAPE, Root Mean Square Error (RMSE)
Results and Analysis
The prediction error statistics over 10 days are shown in the table below:

Table 2. Comparison of prediction errors (MAPE) between ARIMA and LSTM models

Method	MAPE（%）	RMSE
ARIMA	12.5	34.2
LSTM (Proposed)	7.8	18.6

The LSTM model controlled the MAPE for demand prediction within 8%, significantly outperforming the traditional ARIMA model, demonstrating its superiority in predicting highly volatile community logistics demand.

5.4 System Responsiveness Analysis

With the incorporation of the MARL module, the system achieved real-time rescheduling in response to dynamic disturbances such as sudden orders and traffic congestion. The experiments showed:
Dynamic order insertion response time: < 3 seconds
Replanned route adoption rate: > 95%
Overall system scheduling efficiency improvement: ≈22%

5.5 Summary

The simulation experiments validated the significant advantages of the proposed model in route optimization, demand prediction, and system responsiveness. The results demonstrate:
Average delivery time reduced by 18.7%;
Demand prediction error controlled within 8%;
The system exhibits strong real-time responsiveness and collaborative scheduling capabilities.
These results fully support the effectiveness and advanced nature of the proposed intelligent distribution model in practical community logistics applications.

6 Conclusion

The optimization of community logistics distribution is a field of significant importance and considerable challenges. Through BDS technology-based real-time scheduling and route planning, big data analytics-driven demand forecasting and resource allocation, and smart terminal-enabled information sharing and management, distribution efficiency can be enhanced, user demands can be met, and the sustainable development of urban logistics can be promoted. However, challenges such as last-mile delivery difficulties and environmental impact remain to be addressed. Future research should strengthen interdisciplinary collaboration, promote the application of intelligent technologies, advance green logistics initiatives, and enhance the synergy of distribution networks. These efforts will provide support for the innovation and progress of community logistics distribution, ultimately improving the logistics experience of urban residents and contributing to urban sustainable development.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Biographies

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基於北斗技術與智能算法的社區物流配送優化研究

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摘要：隨著社區人口增長和消費需求多樣化，社區物流配送在時效、成本與服務質量等方面面臨嚴峻挑戰。為解決上述問題，本文提出了一種融合北斗衛星導航技術與智能算法的社區物流配送優化模式。通過集成北斗高精度定位與實時交通信息，構建了基於遺傳算法（GA）的路徑優化模型、基於長短期記憶網絡（LSTM）的需求預測模型，以及基於多智能體強化學習（MARL）的實時協同調度算法，實現了配送路徑動態規劃、需求精準預測與資源高效配置。仿真實驗表明，該模式可使平均配送時間降低18.7%，需求預測誤差控制在8%以內，顯著提升配送效率與系統響應能力。本研究為社區物流配送的智能化、綠色化與可持續發展提供了理論支持與技術路徑。

關鍵詞：北斗技術；社區物流；配送模式；遺傳算法；LSTM；多智能體強化學習

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