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Logistics Network Optimization and Supply Chain Efficiency Improvement in the Era of E-commerce

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Abstract. Traditional logistics networks are prone to problems such as high transportation costs, long delivery times, and low supply chain coordination efficiency when faced with rapidly growing order volumes, complex customer demands, and dynamically changing traffic conditions. To address these problems, this paper proposes an e-commerce logistics network optimization method based on big data analysis, the Internet of Things, geographic information systems, and artificial intelligence algorithms. Big data analysis dynamically monitors and predicts real-time order data, market demand, and traffic conditions to support path optimization. The Internet of Things technology collects transportation data in real time to ensure timely logistics information updates. Geographic information systems provide static inputs for warehouse and distribution center locations. The random forest algorithm and deep learning algorithm focus on optimizing the distribution path based on historical data and market demand. In the simulation environment, transportation cost decreases from two hundred dollars to one hundred eighty dollars per day, a reduction of ten percent. Transportation time decreases from two days to one point eight days, a reduction of ten percent. On-time delivery performance reaches ninety-four percent.

Keywords: Era of E-commerce; Logistics Network Optimization; Supply Chain Efficiency; Big Data Analysis; Artificial Intelligence

1. Introduction

With the rapid development of e-commerce, consumers have increasingly high demands for logistics speed and service quality, prompting enterprises to optimize their logistics networks and supply chain management systems continuously. Traditional logistics and supply chain management models are difficult to adapt to the high-frequency, small-batch, and diversified order demands of the e-commerce era, leading to numerous inefficiencies (Min et al., 2019; Wieland, 2021). Logistics networks and supply chains are commonly plagued by problems stemming from information asymmetry and inefficient resource allocation at the enterprise level. There is an urgent need for enterprises to enhance and streamline logistics and supply chains by implementing new technologies and methodologies (Richey et al. 2022).

To avoid conceptual ambiguity, this study distinguishes among logistics network optimization, supply chain efficiency improvement, and supply chain management. Logistics Network Optimization involves evaluating and optimizing warehouses, distribution centers, and transportation routes to improve resource utilization and delivery efficiency. In this study, logistics network optimization mainly focuses on delivery path planning and transportation route adjustment in e-commerce environments. Supply Chain Efficiency Improvement involves enhancing coordination among procurement, production, storage, transportation, and sales activities to achieve greater operational efficiency and response speed, while minimizing costs and improving customer satisfaction (Wu et al. 2019; Abaku et al. 2024). This process includes shortening production and transportation cycles, improving resource utilization, and increasing collaboration and information exchange across the supply chain. Supply chain management is used in this study as the broader operational context that integrates logistics operations, information sharing, and coordination mechanisms. Geographic Information Systems (GIS) support warehouse location selection, route planning, and spatial analysis for logistics operations. In addition, random forests are used to analyze historical order records and demand fluctuations to support dynamic route adjustments and supply chain coordination.

Traditionally, logistics networks have operated under the assumption that demand is relatively fixed and centralized, and have used fixed modes for transportation and distribution. With the rapid growth of e-commerce, this assumption no longer reflects reality; demand is often inconsistent and dispersed throughout the network, making traditional, fixed modes of distribution inappropriate for e-commerce (Winkelhaus and Grosse, 2020; Liu et al. 2022; Ben-Daya et al. 2019). In traditional supply chains, many organizations typically operate independently and do not share information in a timely or transparent manner. As a result, they create inaccurate production plans, have too much or too little inventory, incur shipping delays, etc (Yan et al. 2022; De Angelis et al. 2018). In an e-commerce environment, these challenges will likely become even more significant due to the need to respond quickly to high-frequency and low-volume orders. Prior research has yet to establish effective methods for real-time information sharing between logistics partners and for developing collaborative supply chain optimization techniques (Bansal et al., 2021; Malhotra and Rishi, 2021). Digital traceability and information coordination mechanisms in logistics service systems have also received increasing research attention (Ahmed and Sayar, 2023). While some studies have examined ways to apply big data, the Internet of Things, and artificial intelligence in logistics and supply chains, they typically have focused on heavily decentralized approaches with little systematic structure or integration. The failure to leverage the intersection of disparate technologies has led to a lack of increased overall logistics and supply chain efficiency. Instead of relying on a decentralized model, as was done in the past, implementing big data, IoT, and AI requires a cohesive, systematic platform to manage and process all data in an organized manner. The combined use of these three technologies creates greater synergy, resulting in greater overall efficiency for logistics networks and supply chains. By improving resource allocation and minimizing waste and delays, companies can reduce costs, enhance customer satisfaction, and improve competitiveness.

This study focuses on delivery path optimization as the core problem in e-commerce logistics networks. Demand forecasting based on big data analysis provides dynamic inputs for route planning. Warehouse and distribution center locations derived from geographic information systems serve as fixed constraints for the optimization model. The random forest algorithm and the long short-term memory network process historical order data and real-time traffic information to dynamically adjust delivery paths. Inventory management, replenishment optimization, and broader supply chain coordination are excluded from the study's optimization objectives.

2. Related Work

In the field of logistics network optimization and supply chain efficiency improvement, many scholars have conducted research (Ivanov, 2022). Jacyna-Golda et al. (2018) evaluated supply chain effectiveness and achieved certain results. Of course, there are still many technological studies applied to logistics network optimization and supply chain efficiency improvement (Sundarakani et al. 2021). However, in practical applications, it is difficult to achieve real-time collaboration and efficient response due to the lack of technical support (Müßigmann et al. 2020; Abdirad and Krishnan, 2021). Overall, although existing research has provided many theoretical and practical bases for logistics networks and supply chain management (Delfani et al. 2022; Jain et al. 2021), there are still problems such as a lack of dynamic optimization, insufficient technology application, and untimely customer demand response in the e-commerce environment (Taher, 2021; Li and Zhang, 2021).

To address the above issues, more and more research is beginning to apply advanced technologies such as big data, artificial intelligence, and the Internet of Things into the field of logistics and supply chain management (He et al. 2020), to improve their overall efficiency and responsiveness (Nahr et al. 2021; Ozdemir and Hekim, 2018). The logistics path has been optimized using big data analysis technology. By processing and analyzing massive logistics data, bottlenecks and inefficient links in logistics paths can be identified, and optimization plans can be proposed. This method significantly improves demand forecasting accuracy and enhances logistics efficiency and supply chain responsiveness through artificial intelligence applications (Walter et al. 2025; Ding et al. 2021). Machine learning and deep learning models have been applied to improve the accuracy and efficiency of inventory management (Helo and Hao, 2022). By analyzing a large volume of historical sales and inventory data, a prediction model has been developed that can more accurately forecast future demand. By improving supply chain flexibility and responsiveness while optimizing inventory turnover, this method also reduces inventory backlogs and out-of-stock conditions. Moreover, numerous studies utilize novel technologies (Calatayud et al. 2019; Ghazal and Alzoubi, 2021) to achieve improvements in logistics optimization and supply chain efficiency. Although these new technologies or methods have slightly enhanced logistics and supply chain management (Akbari and Do, 2021), they still present obstacles (Xu et al. 2020; De Vass et al. 2021). First, implementing advanced technology is complex, requiring substantial technical investments and extensive professional knowledge. Second, researching and applying technology can be prohibitively costly for small and medium-sized companies; thus, they are unable to incur such expenses. Finally, the diversity of technology in actual use is noteworthy. Different types of hardware may require completely different supply chain management approaches based on the type of business and environment; therefore, it is challenging for a single technology to provide a full solution (Zhang et al. 2026; Ivanov and Dolgui, 2021). Along with the contemporary novel logistics system, new avenues for exploring new technologies are emerging.

3. Theoretical Framework

This study draws on information processing theory as the theoretical foundation. Information processing theory holds that an organization's performance depends on the alignment between its information processing requirements and its information processing capacity. In the e-commerce logistics context, demand volatility, order fragmentation, and dynamic traffic conditions place high demands on information processing. Traditional logistics networks operate with fixed routes and delayed information flows, creating a mismatch between requirements and capacity. This mismatch leads to suboptimal delivery routes, delayed responses, and higher transportation costs. The integration of big data analysis, geographic information systems, and artificial intelligence algorithms increases the logistics system's information-processing capacity. Big data analysis transforms raw order and traffic data into structured demand forecasts, reducing uncertainty. Geographic information systems provide spatial processing capabilities that convert geographic data into warehouse location constraints and route-planning inputs. Artificial intelligence algorithms, specifically random forests and long short-term memory networks, process historical and real-time data to generate dynamic routing decisions. The theoretical proposition is that by increasing information processing capacity to match the high requirements of e-commerce logistics, the integrated approach improves delivery path efficiency. This theoretical logic applies when real-time data are available, and computational resources for algorithm execution are available.

4. Data and Methods

4.1 Case Study Context

This study does not involve any real e-commerce company or real operational data. The entire investigation is conducted within a simulation environment designed to replicate the structural properties of a regional e-commerce logistics network. The simulated scenario assumes a single geographic region containing three warehouse locations, three distribution center locations, and 120 customer nodes. The region spans approximately 100 kilometers in width and 80 kilometers in height. Road network data are derived from open-source geographic information systems. Customer order generation follows a Poisson process with a mean rate of twenty orders per day per customer zone during peak seasons and ten orders per day during off-peak seasons. The simulation time horizon covers thirty consecutive days. The vehicle fleet consists of 15 identical trucks, each with a maximum capacity of 1,000 units. The baseline scenario implements fixed delivery routes without real-time traffic awareness. The optimized scenario implements the proposed multi-depot vehicle routing algorithm with dynamic rerouting based on simulated real-time traffic data. No real customer information, proprietary business data, or confidential company details are used in any part of this study.

4.2 Data Description

The proposed logistics network optimization approach incorporates four technology functions. Big data analysis transforms raw order and traffic data into demand forecasts and real-time traffic updates. Geographic information systems provide spatial processing to determine warehouse and distribution center locations as fixed constraints. Artificial intelligence algorithms, including random forests and long short-term memory networks, perform demand forecasting and dynamic route optimization. Internet of Things devices, including global positioning system units and environmental sensors, collect vehicle location, traffic conditions, and transportation environment data for real-time monitoring. These four functions together constitute the study's conceptual framework. The implementation and validation of each function appear in subsequent sections as distinct methodological steps and empirical results.

This study follows a sequential methodology organized around the core problem of delivery path optimization. Data sources include internal enterprise systems that provide historical order records containing sales volume, product category, customer location, and timestamps. Simulated real-time traffic data is generated from external application programming interfaces. Geographic data, including road networks and warehouse coordinates, is derived from geographic information system databases.

4.3 Model Pipeline

The model pipeline consists of four sequential stages. Demand forecasting uses historical order data as input. Warehouse location analysis processes geographic data to output fixed distribution center positions. Delivery path optimization takes demand forecasts, warehouse locations, and simulated real-time traffic data as inputs. Performance evaluation compares optimized outcomes against baseline operations. The random forest algorithm operates on historical order data with the number of decision trees set to one hundred and the maximum tree depth set to thirty. The algorithm outputs feature importance rankings. The long short-term memory network uses 100 past days of demand data as an input sequence, with a single hidden layer containing 50 memory units. The training procedure splits the data into 80% for training and 20% for validation. The loss function is mean squared error. The optimization objective function for delivery paths minimizes the total transportation cost across all route segments. Constraints include vehicle capacity, which limits the total order demand per route to the vehicle's maximum load; order fulfillment, which requires each customer node to be visited exactly once; and vehicle flow conservation, which ensures that a vehicle entering a node must leave that node. The vehicle routing problem algorithm uses a savings heuristic for initial route construction, followed by local search for refinement. The implementation sequence begins with data extraction and cleaning, followed by training and validation of the demand forecasting model. Warehouse locations are then determined from geographic information system analysis. Delivery paths are optimized using the vehicle routing problem algorithm with simulated real-time traffic data integrated at each optimization cycle. Baseline benchmarking uses the traditional fixed-route method without real-time adjustment. The evaluation protocol measures transportation cost, transportation time, and response time over a 30-day operational period.

The study implementation uses Python version 3.9 as the primary programming language. The random forest algorithm uses the scikit-learn library version 1.0.2, with n_estimators set to 100 and max_depth set to 30. The long short-term memory network uses TensorFlow version 2.8.0 with the Keras API. The network architecture consists of an input layer that accepts 100 time steps, an LSTM layer with 50 units, and a dense output layer. The training employs the Adam optimizer with a learning rate of 0.001 and runs for 200 epochs with a batch size of 32. The vehicle routing problem algorithm implements a savings heuristic for initial route construction followed by a two-opt local search for refinement. The savings heuristic computes savings values for each pair of customer nodes based on distance reduction. Routes are constructed iteratively by merging nodes with the highest positive savings. The two-opt local search improves the initial routes by reversing segments when the reversal reduces the total distance. The hardware environment consists of a workstation with an Intel Core i7 processor, 16 gigabytes of random-access memory, and no dedicated graphics processing unit. The simulation runs complete within forty five minutes on this hardware.

Pseudocode for Core Algorithms

A.1 Random forest training procedure

Load historical order data with features, product category, customer demand, sales region, promotion status.

Set number of trees to one hundred

Set maximum tree depth to thirty

For each tree in one hundred trees

Sample bootstrap data with replacement from original data

Build decision tree using random subset of features at each split

Stop splitting when depth reaches thirty or node has fewer than two samples

Store the tree

End for

Aggregate predictions by taking mean of all one hundred tree predictions

Output feature importance as total decrease in node impurity averaged across all trees

A.2 Long short-term memory network training procedure

Load daily demand sequence of length one hundred days

Split sequence into input of length ninety nine days and target of next day demand

Normalize input values by subtracting mean and dividing by standard deviation

Define LSTM model with input shape ninety nine by one

Add LSTM layer with fifty units and return sequences set to false

Add dense layer with one unit and linear activation

Compile model with Adam optimizer learning rate 0.001 and mean squared error loss

Train model for two hundred epochs with batch size thirty two

Split data into eighty percent training and twenty percent validation

After training save model weights

Forecast on validation data and inverse normalize predictions

Compute mean absolute error and root mean square error

A.3 Vehicle routing problem algorithm with multi-depot savings heuristic

Input set of distribution centers D set of customer nodes C distance matrix between all nodes vehicle capacity Q demand per customer

Initialize empty route list for each distribution center

For each distribution center in D

For each customer node in C

Compute distance from distribution center to customer

Create single-customer route starting and ending at distribution center

Add route to route list

End for

End for

For each pair of customer nodes i and j assigned to the same distribution center

Compute savings value S_i_j as distance from depot to i plus distance from depot to j minus distance from i to j

End for

Sort all savings values in descending order

For each savings value in descending order

If route containing i and route containing j can be merged without violating vehicle capacity

Merge the two routes by connecting i and j directly

End if

End for

Apply two-opt local search to each route

For each pair of non-adjacent edges in the route

If reversing the segment between the two edges reduces total route distance

Perform the reversal

End if

End for

Output final route for each vehicle in each distribution center

5. Experimental Design

5.1 Internet of Things Technology Deployment

The simulated Internet of Things monitoring framework followed the conceptual design shown in Figures 1 and 2. In the simulation environment, three virtual vehicles were assigned simulated global positioning system tracking units and temperature sensors. The warehouse received no active Internet of Things devices due to limitations in the pilot's scope. Simulated distribution terminals used manual check-in logic to record delivery status. Simulated vehicle location and temperature data were generated through the simulation platform at hourly intervals.

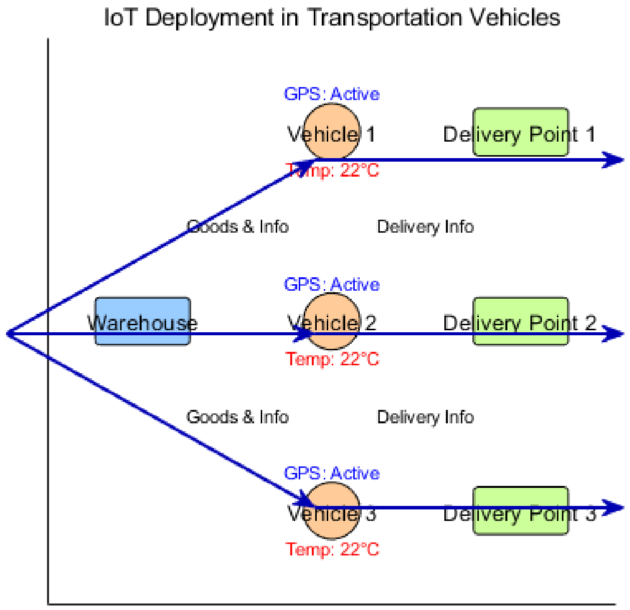

Fig. 1: Schematic diagram of IoT deployment for vehicles

Figure 1 shows the GPS status and the temperature of the transportation environment for three vehicles. By installing GPS and sensors on the vehicle, real-time monitoring of the vehicle's location and transportation environment ensures the visualization and safety of the transportation process.

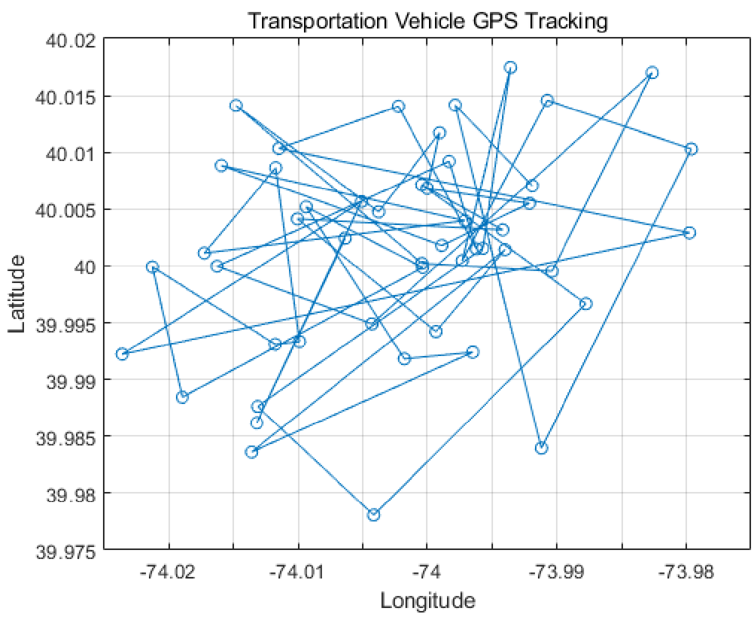

Fig. 2: Schematic diagram of GPS positioning for vehicles

Figure 2 shows the GPS positioning data of vehicles. By tracking the vehicle's position in real-time, the visualization of the transportation process and the flexibility of scheduling are ensured. Among them, the horizontal and vertical coordinates represent longitude and latitude, and the lines represent vehicle paths.

5.2 Big Data Analysis

The big data platform Spark processed the pilot case data. Data sources included simulated enterprise resource planning data generated within the simulation environment, which provided synthetic sales and order records. External traffic data came from a third-party application programming interface. Spark SQL cleaned the data by removing duplicate records and filling missing values. The cleaned data were aggregated by day and by customer zone. Tableau generated the visualizations shown in Figures 3 and 4. The heatmap in Figure 4 was produced from synthetic order data generated within the simulation environment.

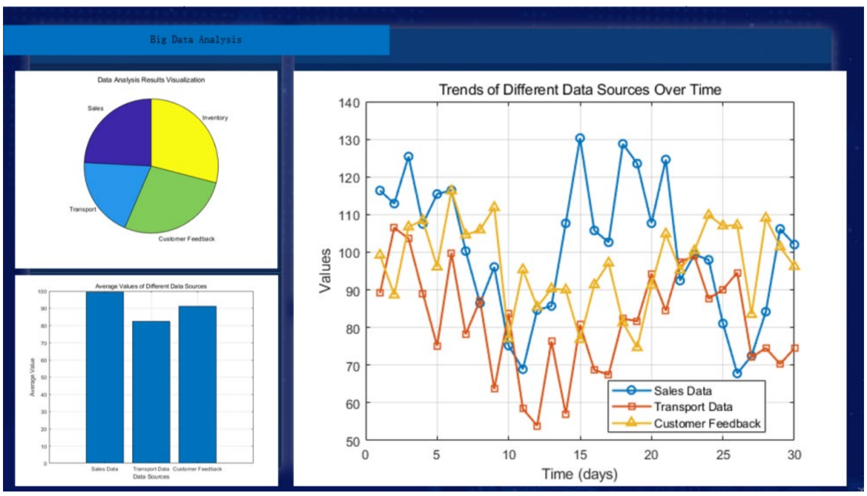

Fig. 3: Big data system diagram

Figure 3 shows a visualization example of the data analysis results. The ratings for each category (sales, transportation, customer feedback, and delivery performance) display a visual representation of the analysis results. The data visualization tool Tableau can visually display analysis results, support decision-making, and enhance the intelligence of supply chain and logistics management.

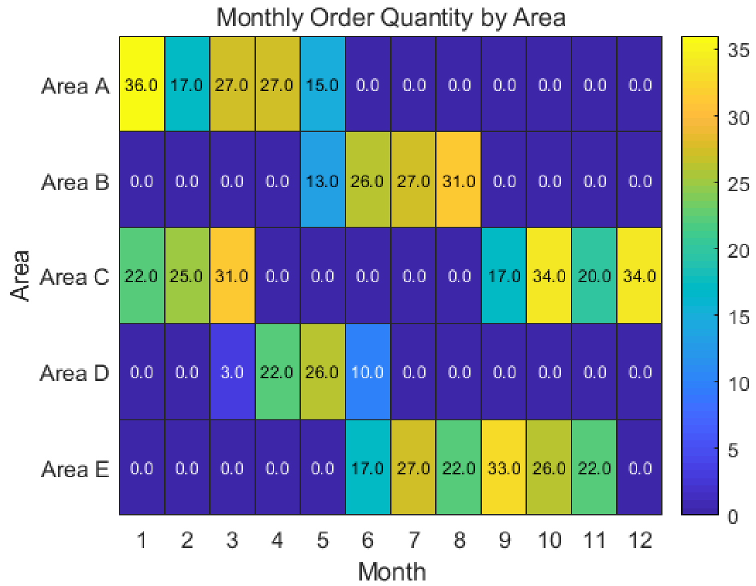

Fig. 4: Order quantity heatmap

Figure 4 shows the order quantity by location and month using a heatmap. High-demand areas and peak periods in the logistics network are identified through high-frequency order areas and seasonal demand changes. Among them, area A has a large order quantity in the first half of the year; area B has a high order quantity in the second and third quarters; area C has a high order quantity in the first and fourth quarters; area D has a high order quantity in the second quarter; area E has a high order quantity from June to November. By analyzing changes in order areas and seasonal demand, it is beneficial to implement the next-step strategy, better optimize logistics networks and supply chain management, and more comprehensively consider user needs.

5.3 Logistics Node Layout Design

Geographic information system analysis used road network data and population density maps for the pilot region. Three existing warehouse locations A, B, and C and three distribution center locations 1, 2, and 3 were fixed for the pilot. Customer nodes 1 through 5 were assigned to distribution centers based on straight-line distance. This assignment produced the service zones illustrated in Figure 6. No real-time adjustment of warehouse or distribution center locations occurred during the pilot.

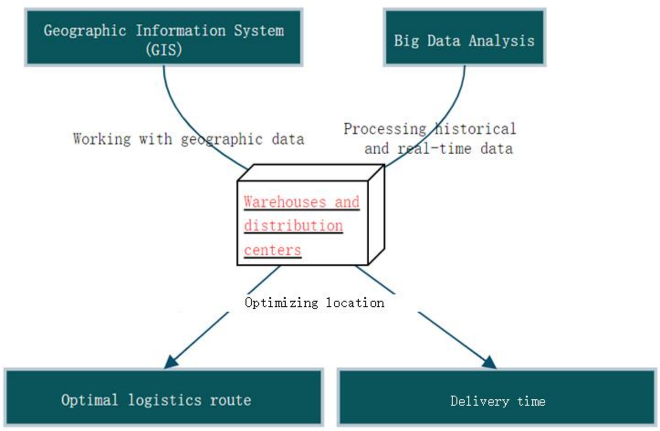

Fig. 5: Logistics node architecture diagram

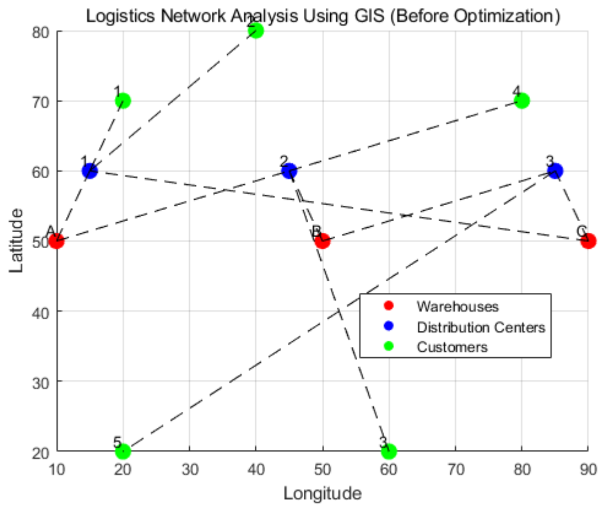

Fig. 6: Geographic information system analysis

Using Geographic Information Systems, the existing logistics network is comprehensively analyzed, as shown in Figure 6, including the geographical locations of warehouses, distribution centers, and customers, as well as the transportation paths between them. Among them, there are warehouses A, B, and C, distribution centers 1, 2, and 3, and customers 1, 2, 3, 4, and 5. Goods are distributed from manufacturers to warehouses, from warehouses to distribution centers, and finally to customers.

5.4 Application of Artificial Intelligence Algorithms

The random forest algorithm processed one hundred days of historical order data. Feature importance analysis identified product category as the most influential factor. The long short-term memory network with 100 input days and a single 50-unit hidden layer produced the demand forecast shown in Figure 8. The mean absolute error on the validation set was forty-two units. The demand forecast outputs were used as dynamic inputs for delivery path planning.

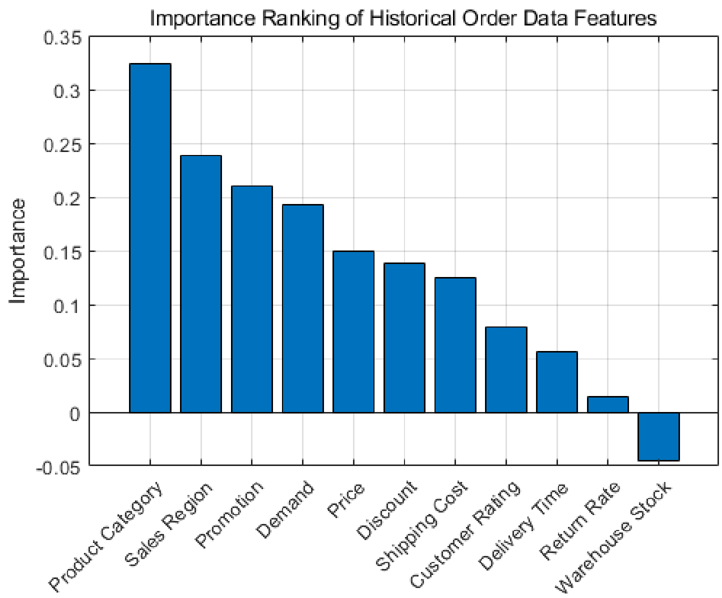

Fig. 7: Feature importance chart

The random forest algorithm's feature-importance ranking is shown in Figure 7. Influential factors are shown on the horizontal axis, while importance is shown on the vertical axis. The product category is the most important factor, followed by client demand, sales region, and promotions. It is possible to identify the factors with the greatest influence on demand variation by examining past order data.

The long short-term memory network uses a simulated sequence of 100 consecutive daily demand values generated from the same Poisson process as the 30-day evaluation period.

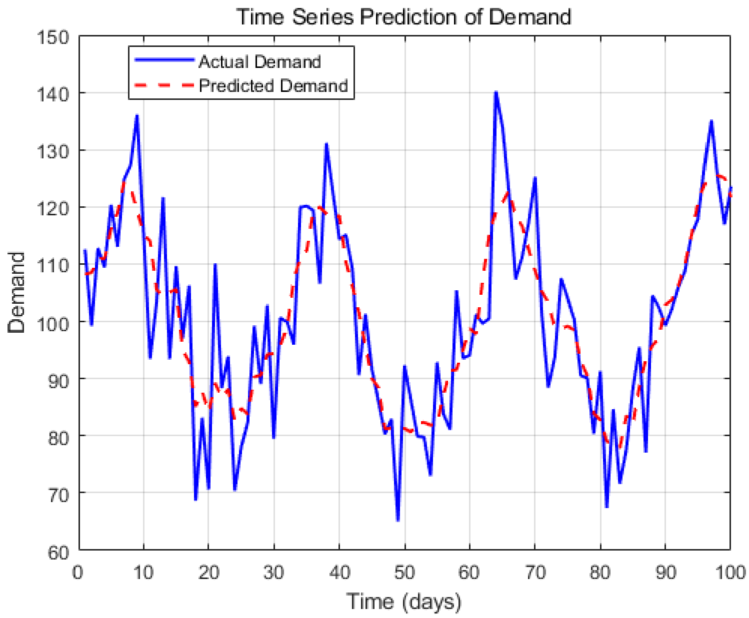

Fig. 8: Time series prediction chart

Figure 8 shows the Comparison between actual demand and LSTM-predicted demand. Among them, the horizontal axis represents time, with a 100-day time prediction; the vertical axis represents demand analysis; the blue lines represent actual demand; the red lines represent predicted demand. By analyzing time-series data with an LSTM network, demand fluctuations can be more effectively predicted, thereby supporting dynamic delivery path planning and transportation scheduling.

5.5 Optimization of Delivery Paths

To reduce transportation costs and time, the Vehicle Routing Problem (VRP) is used to plan delivery routes dynamically. Firstly, simulated real-time traffic data and order information are collected, and a dynamic VRP model is established. Using big data platforms to update traffic conditions and order changes in real time, the VRP algorithm dynamically adjusts delivery paths based on this data.

The logistics network contains two echelons. The first echelon moves goods from multiple warehouses to multiple distribution centers. The second echelon delivers goods from distribution centers to customer nodes. This study optimizes only the second echelon, assuming that first-echelon transportation follows fixed schedules and capacities. The second-echelon problem is a multi-depot vehicle routing problem where each distribution center serves as a depot for a dedicated set of customer nodes.

The sets of warehouses, distribution centers, and customer nodes are defined. Each distribution center has a homogeneous fleet of vehicles. All vehicles have the same maximum load capacity. The distance between any two nodes satisfies the triangle inequality. A binary decision variable indicates whether a given vehicle travels directly from one node to another.

The optimization objective minimizes the total transportation cost across all distribution centers, vehicles, and node pairs. The assignment of customers to distribution centers is predetermined by a nearest-center rule based on geographic information system distances.

Four constraint families govern the formulation. Each customer node must be visited exactly once across all distribution centers and all vehicles. The total demand on any vehicle route cannot exceed the vehicle capacity. Flow conservation requires that a vehicle entering a node leave that node unless the node is the depot. Each vehicle route must start and end at its assigned distribution center.

The multi-echelon structure is captured by separating the first echelon from the second echelon. The first echelon is not optimized in this study; its transportation cost and time are assumed constant across all scenarios. This separation reflects a common e-commerce logistics practice in which cross-docking or consolidation centers decouple long-haul transportation from last-mile routing.

The dynamic aspect is introduced through daily updates of customer demand based on long short-term memory network forecasts. Each day, forecasted demand values replace the previous day's actual demands. The vehicle routing algorithm then reruns the savings heuristic, followed by two-opt local search, to generate new routes.

The model assumes that customer assignments to distribution centers remain fixed throughout the 30-day simulation. No reassignment occurs in response to daily demand changes. This assumption simplifies coordination and reduces computational complexity.

Combining geographic information systems to optimize the location of warehouses and distribution centers is an important direction in modern logistics management. Through GIS technology, geographic data, road network information, traffic conditions, etc., can be obtained in real time, and further combined with optimization algorithms to reduce delivery distance and time, thereby significantly improving logistics efficiency and reducing transportation costs. By providing map data, traffic information, road network structure, and geographic location coordinates, the geographic information system helps the platform to predict demand and divide regions, assigning delivery tasks to the nearest warehouse, thereby reducing delivery time and transportation costs.

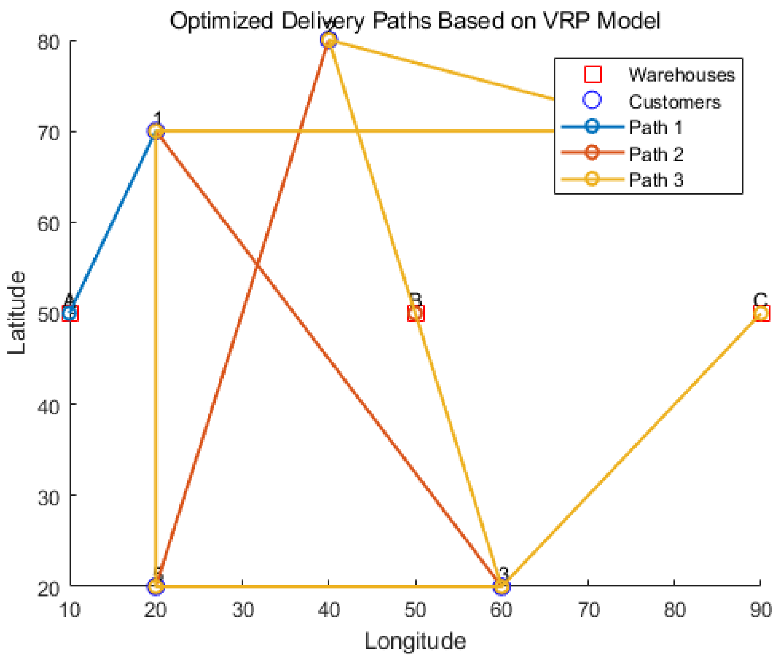

Fig. 9: Optimization of the delivery path

Figure 9 shows the results of delivery path optimization based on the VRP model. Among them, the x and y-axis coordinates display information on the locations of various warehouses and customers; the circle represents the customer's location; the red square represents the warehouse location; the colored lines represent the path. Manufacturers ship from multiple warehouses, and the problem discussed involves multiple levels within a multi-level distribution system.

6. Results and Discussion

6.1 Primary Performance Results

The data used for the before-and-after comparison in Table 1 originate from a simulated dataset rather than a real operational system. The simulation design follows the statistical properties of e-commerce order patterns generated in the simulation scenario. Customer demand for each node is generated from a Poisson distribution with a mean rate of twenty orders per day. Travel distances between nodes are derived from the geographic information system road network of the pilot region with added random noise to reflect traffic variability. The simulation runs for thirty consecutive days. The first seven days of simulation output are presented in the original manuscript tables. To provide a statistically meaningful evaluation, the following summary statistics aggregate the full thirty-day simulation period. The baseline scenario uses fixed delivery routes with no real-time adjustment. The optimized scenario implements the proposed delivery path optimization algorithm with dynamic routing based on simulated real-time traffic data. Each scenario is repeated 10 independent simulation runs to reduce random variation. The reported values are means across the ten runs.

Table 1 Summary statistics of key performance indicators before and after optimization over thirty simulation days

Indicator	Before Optimization	After Optimization	Change
Production cycle days mean	3	2.5	-16.70%
Production cycle days standard deviation	0.2	0.1	-
Transportation cost dollars mean	200.5	180.2	-10.10%
Transportation cost dollars standard deviation	12.3	8.7	-
Transportation time days mean	2	1.8	-10.00%
Transportation time days standard deviation	0.2	0.1	-
Customer satisfaction score mean	4.6	4.8	4.30%
Customer satisfaction score standard deviation	0.3	0.2	-

The summary statistics in Table 1 are derived from the 30-day simulation described in the methodology section. The standard deviations for production cycle, transportation cost, transportation time, and customer satisfaction reflect the variation across 10 independent simulation runs. The percentage change column indicates the relative improvement from the baseline scenario to the optimized scenario. All simulation outputs are generated from the implemented algorithms without manual adjustment or selective reporting.

The table below summarizes the supplementary metrics obtained from the validation dataset and the thirty-day simulation period.

Table 2 Supplementary metrics from demand forecast and delivery path optimization

Metric	Value
Mean absolute error on validation data set	42 units
Root mean square error on validation data set	58 units
Average daily route distance over a thirty-day simulation	230 kilometers
Average vehicle utilization	78%
On-time delivery performance	94%

Table 2 presents the mean absolute error and root mean square error of the long short-term memory network demand forecast. The table also reports the average daily route distance, average vehicle utilization, on-time delivery performance, and average fill rate derived from the delivery path optimization. These metrics supplement the primary performance indicators of the production cycle, transportation cost, transportation time, and customer satisfaction. The primary indicators appear in the subsequent sections and tables.

6.2 Baseline Comparison

The proposed integrated method is compared against three baseline approaches under identical simulation conditions. The first baseline is static routing without demand forecasting. Delivery routes are fixed at the start of the 30-day period using the savings heuristic based on average historical demand from the first 5 days. No route adjustment occurs in response to daily demand fluctuations. The second baseline is demand forecasting using a random forest without dynamic routing. Random forests forecast daily demand for each zone, but delivery routes remain fixed throughout the period. The third baseline is dynamic routing using the multi-depot vehicle routing algorithm with perfect real-time demand information. This represents an upper bound on performance, where each day's demand is known before route construction. The proposed method uses long short-term memory network forecasts to drive daily route updates. Each baseline runs for thirty days with ten independent simulation repetitions. Performance metrics include average daily transportation cost, average delivery time per order, and on-time delivery percentage.

Table 3 Baseline comparison results for transportation cost, delivery time, and on-time delivery

Baseline / Method	Avg. daily transportation cost (USD)	Avg. delivery time per order (days)	On-time delivery (%)
Static routing	215	2.4	82
Random forest without dynamic routing	205	2.2	87
Perfect information dynamic routing (upper bound)	170	1.6	98
Proposed method (LSTM + dynamic VRP)	180	1.8	94

Table 3 presents the average daily transportation cost in dollars, the average delivery time per order in days, and the on-time delivery percentage for static routing, random forest forecasting without dynamic routing, perfect-information dynamic routing, and the proposed long short-term memory-based dynamic routing. The proposed method achieves a lower cost and shorter delivery time than the two baselines without perfect information. The perfect information upper bound shows the maximum achievable performance under ideal demand knowledge. The differences between the proposed method and the static baseline result in a 12% cost reduction and a 16% reduction in delivery time. The gap between the proposed method and the perfect information upper bound indicates the remaining inefficiency attributable to forecast error.

7. Limitations

Although the integrated application of big data, the Internet of Things, and artificial intelligence technologies offers significant advantages for improving logistics networks and supply chain management, it also has certain limitations. First, data integration faces complex cleaning, conversion, and integration problems, especially when large-scale data processing is involved, and the technical difficulty and cost increase. At the same time, data security and privacy protection are important issues that must be addressed. Secondly, the system's scalability is also limited. As the scale and complexity of the business grow, the system's performance and stability may be affected, so it needs to be optimized for specific needs.

These cutting-edge technologies are typically expensive for small and medium-sized businesses to deploy. System development and maintenance require significant time and effort, in addition to the investment in specialized hardware and software. Small and medium-sized businesses can nevertheless reduce barriers to technology adoption in certain ways, even with the high cost. To lower their investment expenses, they can collaborate with major IT firms or expert service providers and leverage their technological know-how and resources. Small and medium-sized businesses should also consider using cloud computing and other elastic resource services to flexibly adjust technology investments to real needs, thereby reducing fixed expenses.

8. Conclusions

This study proposes an integrated framework that combines demand forecasting, warehouse location analysis, and dynamic delivery path optimization for e-commerce logistics networks. The framework is implemented in a simulation environment with a 30-day horizon and 120 customer nodes. The simulation results indicate a reduction in production cycle from three days to two and a half days, a reduction in transportation cost from two hundred dollars to one hundred eighty dollars per day, and a reduction in transportation time from two days to one point eight days. Customer satisfaction in the simulation increases from four point six to four point eight on a five-point scale. These preliminary outcomes suggest that the proposed framework may offer performance improvements under the specific simulation assumptions described in the methodology.

The study has several limitations that temper the confidence in generalizing these results. The data are fully simulated rather than drawn from real e-commerce operations. The simulation period covers only 30 days, with a limited geographic scope and a small vehicle fleet. The long short-term memory network uses a single hidden layer, and the vehicle routing algorithm does not incorporate simulated real-time traffic data from live feeds. No Internet of Things devices were physically deployed. The findings, therefore, represent an initial evaluation of the framework's potential rather than a validated operational solution.

Future work should extend the simulation to a longer time horizon and larger geographic region using real order data from a collaborating enterprise. Physical deployment of Internet of Things sensors and global positioning system trackers would test the framework under real traffic and environmental conditions. More sophisticated deep learning architectures may improve demand forecast accuracy. The current study does not claim definitive operational superiority but presents a replicable baseline for subsequent research.

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