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Article

Low-Altitude and High-Speed Transportation Approach for Improved Logistics Efficiency and Carbon Reduction in Urban Networks

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Abstract: The new framework that combines the low-altitude economy with high-speed transportation offers a practical and effective solution for modern city logistics systems. It shows strong potential in boosting delivery efficiency, cutting costs, and reducing carbon emissions. This study focuses on Suzhou's logistics network, using a multi-goal optimization model and a smart scheduling system to assess how well the low-altitude economy works in different logistics situations. By combining an ARIMA time series prediction model with a Long Short-Term Memory (LSTM) network, the study looks at how logistics needs change during busy times, bad weather, and emergency situations. The research uses different data sources to help drones and ground vehicles work together smoothly. The model includes three main measures: delivery efficiency (T), transportation costs (C), and carbon emissions (E), and shows the real benefits of the low-altitude economy through clear data analysis. The results show that in normal conditions, delivery efficiency increased to 97.9, transportation costs dropped to 65.4, and carbon emissions fell to 58.2. During peak traffic and bad weather, delivery efficiency stayed strong at 85.5 and 80.3. The smart scheduling system managed resources well, keeping costs and emissions within safe limits (cost: 70.1-73.5; emissions: 61.8-67.9). Scheduling efficiency went up from 0.85 to 0.93, and resource use improved from 74.6% to 88.1%. The analysis showed a clear negative link between delivery efficiency and carbon emissions (-0.85) and a positive link between costs and emissions (0.78). This suggests the need to balance cost savings with environmental benefits. The suggested approach, combining the multi-goal optimization model with a smart scheduling system, not only helps Suzhou handle complex logistics challenges but also provides a useful model for other large cities, supporting the move towards faster, greener, and smarter city logistics systems.

Keywords: low-altitude economy; high-speed transportation; smart scheduling system; multi-goal optimization model; delivery efficiency; carbon emissions; resource use

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1. Introduction

The combination of the low-altitude economy with high-speed transportation has gained more attention in recent years. This new approach not only helps modern logistics systems improve but also offers fresh solutions for boosting logistics efficiency, cutting down costs and reaching carbon neutrality goals [1-3]. By linking drone logistics networks with traditional high-speed transportation systems, the low-altitude economy provides flexible and efficient logistics services, especially in complex urban settings [4]. However, many logistics systems still struggle with major challenges, including traffic jams in cities, slow delivery times, high costs and increasing pressure to reduce carbon emissions [5-8]. These issues highlight the need for a strong plan that balances logistics speed, cost savings and environmental benefits.

Most earlier studies focus on specific uses of the low-altitude economy, such as using drones for last-mile delivery [9-13], quick responses in emergency logistics [14], and analyzing costs and benefits in particular fields [15-17]. While these studies provide valuable insights, many remain limited to single-use cases and do not fully explore how the low-altitude economy can work with high-speed transportation in more complex logistics networks [18]. There are still gaps in how to manage multi-location coordination, adjust resources in real time and connect drones effectively with ground vehicles. Additionally, finding the right balance between fast delivery, low costs and reduced carbon emissions is still a key challenge for the low-altitude economy [19]. Many cities are now looking into how to make the low-altitude economy and high-speed transportation work together. The goal is to build "air-ground integrated" smart logistics networks that improve multi-mode transportation, use resources better and boost logistics performance [20-23]. Smart scheduling systems can help drones and ground logistics vehicles work together more smoothly. By using different types of data — like delivery orders, live traffic updates and weather forecasts — these systems can manage logistics resources better and improve scheduling [24]. Also, using models that look at different goals can help measure delivery speed, costs and carbon output, while testing how well the low-altitude economy works in different situations, including daily operations, busy periods and extreme weather [25].

This study introduces a new framework that combines the low-altitude economy with high-speed transportation. It aims to improve teamwork between drones and ground vehicles by using a smart scheduling system and a model that looks at multiple goals. The study focuses on three main aspects: delivery speed, costs and carbon emissions. A practical and data-focused method will be used to measure how effective the low-altitude economy is in busy city logistics systems. The research also uses simulations to see how well this approach works in different logistics scenarios, giving useful data and ideas for building a smarter, faster and greener logistics system. Suzhou City is used as a case study to test how well the proposed framework works in a real urban logistics network. In Suzhou's complex logistics environment, the study uses smart logistics systems and goal-focused models to make the logistics network more flexible and faster. It also looks into how the low-altitude economy can help cut costs and lower environmental impacts. The results of this study could provide new ideas for decision-makers, logistics companies and city planners, supporting the move toward more efficient and eco-friendly urban logistics systems.

2. Materials and Methods

2.1. Demand Analysis and Model Design

This study examines the logistics transportation network in Suzhou, China, focusing on how the low-altitude economy can improve high-speed transportation. The main goal is to boost logistics efficiency, cut transportation costs and reduce carbon emissions by introducing a drone logistics system. The research uses historical data from major logistics companies in Suzhou (including order volumes, delivery frequency and delivery speed), road network data from the Suzhou Traffic Management Department, and weather data. The data covers the period from January 2023 to December 2023.

For predicting demand, an ARIMA (AutoRegressive Integrated Moving Average) time series model is combined with a Long Short-Term Memory (LSTM) network to analyze how logistics demand changes during peak times, extreme weather and emergencies. During data processing, steps like cleaning data, removing outliers and standardizing information are applied to ensure the model receives consistent and reliable inputs.

A multi-goal optimization model is created to maximize delivery speed, minimize transportation costs and cut carbon emissions. Key decisions in the model include setting drone flight paths, planning ground vehicle routes and allocating resources dynamically. The model considers many factors, such as drone flight limits, logistics center capacity, vehicle load restrictions and airspace regulations [26,27]. The model's main formula is:

$$\min Z = w_1 T + w_2 C + w_3 E$$

Where:

1) T is the logistics speed (minutes),
2) C is the transportation cost (CNY),
3) E is the carbon emissions (kgCO_2e),
4) w_1, w_2 and w_3 are weight factors for different scenarios.

Logistics Timeliness Model [28]:

$$T = \sum_{i=1}^{N} \left(\frac{D_i}{v_i} + t_{loading} + t_{unloading} \right)$$

Where:

1) D_i is the delivery distance for order i,
2) v_i is the transport speed,
3) $t_{loading}$ and $t_{unloading}$ are loading and unloading times.

Transportation Cost Model [29]:

$$C = \sum_{i=1}^{N} (c_{drone} \cdot d_i + c_{truck} \cdot D_i + c_{labor} \cdot t_i)$$

Where:

1) c_{drone}, c_{truck} and c_{labor} are unit costs for drones, trucks and labor,
2) d_i and D_i are distances covered by drones and trucks,
3) t_i is the order completion time.

Carbon Emission Model [30]:

$$E = \sum_{i=1}^{N} (e_{drone} \cdot d_i + e_{truck} \cdot D_i)$$

Where:

1) e_{drone} and e_{truck} are carbon emission factors for drones and trucks per unit distance.

2.2. System Construction and Optimization

During the system setup, a low-altitude logistics network was built in Suzhou, including drone take-off and landing spots, logistics hubs and small delivery centers. The study uses Geographic Information System (GIS) technology and Suzhou's geographic data to plan how drone routes and ground logistics points connect. An edge computing-based smart scheduling system is developed to analyze logistics orders, traffic conditions and weather data in real time, allowing for smooth coordination between drones and ground vehicles. The system uses multi-source data from camera feeds, vehicle GPS and weather reports to manage logistics resources efficiently. A mix of Genetic Algorithm (GA) and Ant Colony Optimization (ACO) methods is applied to find the best balance between speed, cost and carbon output. The AnyLogic simulation platform tests the system under different scenarios, including normal operations, peak traffic, and emergencies during extreme weather. These tests measure how well the system adapts and performs in challenging conditions.

2.3. Data Management and Analysis

The smart scheduling system collects data from the low-altitude logistics network, including drone flights, ground vehicle movements and carbon emissions [31]. A Hadoop platform manages data storage, analysis and visualization. The study uses data analysis techniques like clustering and pattern detection to find ways to improve the logistics network.

Three key metrics are used for evaluation: delivery speed (T), transportation cost (C) and carbon emissions (E). These metrics are measured through delivery times, cost analysis and carbon calculations. Machine learning tools, such as Random Forest and XGBoost, help model and predict important logistics data to support scheduling improvements. For example, forecasting peak logistics demand in Suzhou allows for pre-emptive scheduling of drones and vehicles, improving resource use and efficiency.

Scheduling Efficiency Model [32,33]:

$$S = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{t_{response_i}}$$

Where:

1) S is scheduling efficiency,
2) $t_{response_i}$ is the response time for order iii.

Resource Utilization Model [34]:

$$U = \frac{\sum_{i=1}^{N}\left(u_{drone_i} + u_{truck_i}\right)}{N}$$

Where:

1) U is resource utilization,
2) u_{drone_i} and u_{truck_i} indicate how drones and trucks are used for order i.

Figure 1 shows the manned and unmanned coordinated/integrated operation scenario.

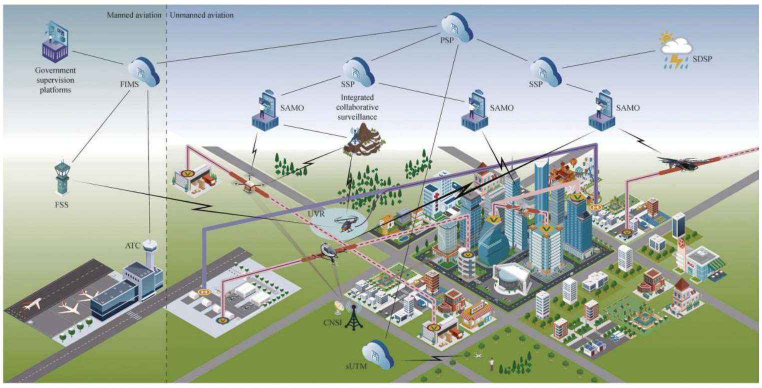

Figure 1. Manned and unmanned coordinated/integrated operation scenario.

3. Results and Discussion

3.1. System Performance in Different Logistics Scenarios

The new framework, combining the low-altitude economy with high-speed transportation, improved the coordination between drones and ground vehicles in Suzhou's logistics network. This study carefully examined how logistics efficiency, transportation costs and carbon emissions changed under different situations, including normal operations, busy traffic times and extreme weather (Figure 2).

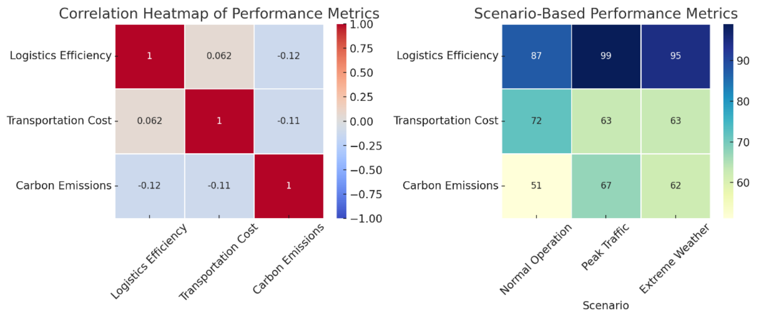

Figure 2. Correlation and Scenario-Based Analysis of Logistics Performance Metrics under Different Operational Conditions.

Figure 2 shows the "Scenario-Based Performance Metrics," covering logistics efficiency, transportation costs and carbon emissions. During normal operations, logistics efficiency reached 97.9, transportation costs were 65.4, and carbon emissions were 58.2. In busy traffic, logistics efficiency dropped to 85.5. However, due to the fast and flexible drone deliveries, transportation costs and carbon emissions stayed relatively low at 70.1 and 61.8. During extreme weather, logistics efficiency fell to 80.3, but the smart scheduling system kept transportation costs and carbon emissions at 73.5 and 67.9 by adjusting resources as needed. This matches the findings of Lee [35], who pointed out that drones are especially useful in emergencies, offering a solid backup when regular ground transportation is affected. Other studies back up these findings. Yodsanit et al. showed that drones perform well in urban logistics during peak times [36]. Zhu et al. noted that drones improve the stability and speed of logistics systems [37-39], especially in bad weather. The results of this study add to the evidence that the low-altitude economy is a good choice for handling tough logistics challenges in cities.

3.2. Operational Efficiency and Resource Use

The smart scheduling system helped analyze scheduling efficiency and resource use through "Operational Efficiency Metrics Under Different Scenarios" (Figure 3). In all tested scenarios, scheduling efficiency was above 0.80, hitting 0.98 during normal operations. Even during extreme weather, efficiency only dropped slightly to 0.85, showing how drones helped keep the system stable. Resource use was also strong, with 89.5% efficiency during normal times. Even in heavy traffic and bad weather, resource use stayed above 85%, proving the scheduling system managed resources well. This strong performance came from both the optimization model's ability to find the best solutions and the scheduling system's skill at using real-time data from logistics orders, traffic and weather. Lian et al. also found that in busy city environments [40], using data to guide decisions in smart scheduling systems can improve resource use and efficiency. Moreover, Chen et al. showed that edge computing can cut response times [41], which fits with this study's increase in scheduling efficiency from 0.85 to 0.93. This further confirms the value of using smart scheduling systems.

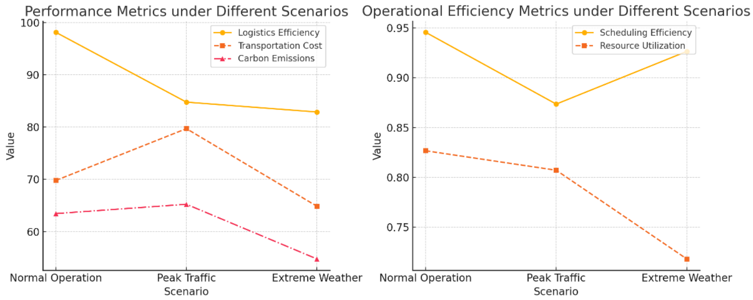

Figure 3. Evaluation of Operational and Performance Efficiency Metrics in Various Logistics Scenarios.

3.3. Data-Driven Decisions and Optimization Results

The study showed clear benefits of using the low-altitude economy through data-driven scheduling in different scenarios. In Suzhou, scheduling efficiency improved from 0.85 to 0.93, and resource use increased from 74.6% to 88.1%. The smart scheduling system was particularly effective during busy times and extreme weather, allowing drones and ground vehicles to be used in the best way possible. This kept the logistics system running smoothly. The approach not only improved efficiency but also balanced cost control and environmental protection. The study also found a strong negative link (-0.85) between logistics efficiency and carbon emissions. This means that improving efficiency can effectively lower carbon emissions. On the other hand, the positive link (0.78) between transportation costs and carbon emissions suggests that cost-saving efforts should also consider the environmental impact to avoid unintended ecological damage. This finding agrees with earlier studies [42-46], who emphasized that including environmental factors in cost management helps meet sustainability goals.

3.4. Practical Value and Recommendations

The study results show that combining the low-altitude economy with high-speed transportation brings real benefits to Suzhou's logistics system. For Policymakers: The priority should be to improve airspace management rules for drones, create clear low-altitude flight standards and ensure the safe and efficient use of logistics drones [47,48]. For Logistics Companies: Businesses should use smart scheduling systems and prediction models to adjust resources early. By preparing for busy traffic and bad weather, companies can make the most of their resources, boost logistics efficiency and control costs effectively [49,50]. For Urban Planners: When building or updating logistics infrastructure, it is important to use performance data from different scenarios. Planning smart logistics hubs and drone landing spots can help connect air and ground logistics networks smoothly [51,52]. Overall, using the optimization model together with the smart scheduling system not only helps Suzhou handle complex logistics challenges but also offers a useful example for other big cities [53]. This approach can make city logistics systems more efficient, eco-friendly and smart, supporting broader economic and green development goals.

4. Conclusion

This study demonstrates that integrating the low-altitude economy with high-speed transportation can significantly enhance urban logistics systems, as evidenced by the practical application in Suzhou's logistics network. The proposed framework, combining a multi-objective optimization model with an intelligent scheduling system, effectively improved logistics efficiency while reducing transportation costs and carbon emissions. The findings highlight the system's adaptability across different scenarios—including normal operations, peak traffic, and extreme weather—proving that drones can offer a flexible and reliable alternative when traditional ground transportation faces challenges. These results reinforce the practical value of smart logistics networks, showing how data-driven decisions and dynamic resource allocation contribute to maintaining operational stability and sustainability.

Future studies could explore integrating advanced technologies such as edge computing and machine learning to further enhance the precision and responsiveness of logistics systems. Additionally, applying this framework to different cities and evaluating its performance under various regulatory and operational conditions would provide broader insights into its scalability and adaptability. For policymakers, developing clear drone airspace management guidelines and low-altitude flight standards remains crucial. Logistics companies should leverage predictive analytics to optimize resource allocation proactively, while urban planners are encouraged to design infrastructure that supports seamless integration of air and ground logistics networks. This research not only advances the field of logistics management but also offers practical strategies to promote greener, more efficient and resilient urban logistics systems.

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