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Smart Parcel Delivery Risk Prediction and Adaptive Route Optimization system

Mrs. R. Geethanjali[1] , Mr.Sujith C[2] , Mr.Mayuranathan T[3],Mr.kunguma Sanjai G [4]

Assistant Professor[1] ,students[2 3 4] , Department of Computer Science and Engineering,
Angel College of Engineering and Technology, Angel nagar, P.K.Palayam, Tiruppur , Tamil Nadu, India

geetha9922@gmail.com, sujithstrat@gmail.com, tmayuranathan295@gmail.com*, Kungumasanjai2015@gmail.com*

ABSTRACT

The Smart Parcel Delivery Risk Prediction and Adaptive Route Optimization System is designed to revolutionize the logistics and supply chain industry by minimizing delivery delays and maximizing efficiency. This system leverages advanced machine learning techniques to predict potential delivery risks, such as adverse weather conditions and varying traffic volumes, while also predicting customer availability to ensure successful first-time deliveries. Furthermore, it incorporates a hybrid algorithmic approach—combining Dijkstra's algorithm for shortest-path calculation and a Genetic Algorithm for multi-stop sequence optimization—to dynamically generate the most efficient delivery routes. By integrating these predictive and optimization modules into a cohesive platform, the system significantly reduces operational costs, enhances delivery personnel efficiency, and improves overall customer satisfaction.

This survey emphasizes the need for intelligent delivery risk prediction and adaptive route planning to reduce last-mile delivery failures and delays.

KEYWORDS

Smart Delivery, Delivery Failure Prediction, Machine Learning, Artificial intelligence Route Optimization, Genetic Algorithm, Logistics Management, Smart Transportation.

I. INTRODUCTION

In the era of rapidly expanding e-commerce and on-demand services, last-mile parcel delivery has become a crucial component of modern logistics systems. With increasing delivery volume, computational techniques and Machine Learning (ML) models are being widely explored to improve delivery efficiency, reduce operational cost, and enhance customer satisfaction. This survey paper examines state-of-theart approaches for delivery failure risk prediction and adaptive route optimization, highlighting the role of algorithms such as Logistic Regression, Random Forest, Decision Trees, and Evolutionary Genetic Algorithms in solving real-world delivery challenges.

A major gap in existing delivery research is the limited integration of predictive risk analytics with real-time, adaptive route planning. While many systems focus on shortest-path navigation or static scheduling, they often fail to handle real-world uncertainties such as traffic congestion, customer unavailability, incorrect addresses, and time-window constraints.

This survey addresses this gap by presenting an integrated perspective that combines ML-based delivery risk prediction with adaptive route optimization frameworks, enabling smarter decision-making and improving the reliability of last-mile delivery operations.

A. Core Themes of This Survey

The paper is structured around four core themes:

- **Machine Learning & AI-Based Prediction Models:** A review of ML techniques used to predict delivery failures, delays, and risk levels using historical and operational delivery data.
- **Route Optimization & Scheduling Algorithms:** Study of optimization methods such as shortest path models and evolutionary algorithms to generate efficient delivery and pickup routes.
- **Last-Mile Logistics Challenges & Risk Factors:** Analysis of real-world delivery issues like traffic congestion, customer unavailability, incorrect addresses, weather impact, and time-window constraints.
- **Smart Logistics Systems & Decision Support Tools:** The role of intelligent dashboards, real-time monitoring, and automation in improving delivery performance and supporting logistics managers.

By consolidating existing research and proposing an integrated risk-aware routing framework, this survey bridges the gap between predictive models and practical delivery operations, providing a foundation for future advancements in intelligent logistics and smart transportation systems.

II. REVIEW OF EXISTING RESEARCH PAPERS

The field of last-mile parcel delivery optimization has gained significant attention with the rapid growth of e-commerce and urban logistics. Recent research has increasingly focused on applying Machine Learning (ML) and optimization techniques to predict delivery delays, failures, and to improve route efficiency. Studies have explored the use of ML models such as Logistic Regression, Decision Trees, Random Forests, and Support Vector Machines (SVMs) to analyse historical delivery data and identify risk factors affecting delivery success.

Breiman introduced Random Forest as a powerful ensemble learning technique capable of handling complex and high-dimensional datasets, making it suitable for logistics applications involving multiple delivery variables. Several studies have demonstrated that Random Forest models outperform traditional statistical methods in predicting delivery delays and failures due to their robustness and reduced overfitting. Similarly, Decision Tree models have been used to provide interpretable insights into delivery outcomes by identifying critical factors such as delivery time windows, traffic congestion, and customer availability.

In parallel, route optimization has been widely studied using heuristic and evolutionary algorithms. Genetic Algorithms (GA) have been applied to vehicle routing problems, pickup and delivery scheduling, and drone-based parcel delivery systems. Research findings indicate that GA-based routing methods significantly reduce total travel distance, delivery time, and operational cost when compared to static shortest path routing approaches. These algorithms are particularly effective in handling dynamic constraints and multi-objective optimization problems in logistics environments.

A. Comparison of Past Methodologies

Existing methodologies for parcel delivery optimization and failure management can be broadly categorized into the following approaches:

- **Rule-Based and Manual Planning Systems:** Traditional delivery systems rely on predefined rules, manual scheduling, and static route assignments. These approaches commonly use fixed delivery zones and shortest-path routing, which fail to handle dynamic delivery constraints such as traffic congestion, customer unavailability, and time-window variations.
- **Operations Research and Heuristic Models:** Classical optimization techniques such as the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) models have been widely used to minimize delivery distance and cost. While effective in structured environments, these methods struggle with scalability and real-time adaptability when faced with dynamic delivery conditions.
- **Machine Learning (ML) Models:** Machine learning models use past delivery data to predict the result.

improvements in route efficiency and delivery time reduction compared to static routing methods. Despite the effectiveness of ML-based prediction and optimization techniques, most existing methodologies address delivery risk prediction and route optimization as independent processes. The lack of integrated, risk-aware routing frameworks limits their real-world applicability, highlighting the need for unified systems that combine predictive analytics with adaptive route optimization for efficient last-mile delivery management.

III. STRENGTHS AND WEAKNESSES OF EXISTING APPROACHES

A. Strengths

- For example, several logistics studies have employed Random Forest models to predict delivery success based on factors such as traffic conditions, delivery time slots, and customer availability, achieving higher prediction accuracy than traditional statistical models. Similarly, Genetic Algorithms have been applied to vehicle routing and pickup– delivery scheduling problems, showing significant
- **Machine Learning Models (RF, LR, DT):** These models are effective in analysing historical delivery data and identifying delivery failure risks. Random Forest models are robust against overfitting and provide reliable predictions for complex, high-dimensional logistics datasets.
- **Route Optimization Algorithm:** Optimization techniques such as Genetic Algorithms and heuristic routing models help minimize delivery distance, time, and fuel consumption, improving operational efficiency in last-mile delivery.
- **Data Driven Decision Making:** ML-based delivery systems enable logistics operators to make informed decisions by analysing traffic conditions, delivery time windows, and customer availability patterns.

B. **Traditional Machine Learning Approaches**

Traditional Machine Learning (ML) algorithms have been widely applied in parcel delivery analysis due to their efficiency and interpretability when handling structured logistics data. Logistic Regression is commonly used for binary classification of delivery success and failure, while Decision Trees provide transparent rule-based decision structures. Random Forest models improve prediction accuracy by combining multiple decision trees and reducing variance.

Despite their advantages, traditional ML approaches have certain limitations. These models rely heavily on historical structured data and often require manual feature engineering to achieve optimal performance. In addition, model accuracy can be affected by data imbalance and changing real-world delivery conditions. Nevertheless, traditional ML models remain effective for delivery risk prediction and form the foundation for intelligent logistics and route optimization systems.

IV. Machine Learning-Based Models

Machine learning–based models are employed to analyse historical and operational delivery data to predict potential delivery failures and delays. Structured delivery attributes such as delivery distance, time slot, traffic condition, customer availability, and past delivery outcomes are used as input features for model training. Supervised learning techniques are preferred due to their effectiveness in classification-based

while Random Forest improves prediction accuracy and robustness by combining multiple decision trees. These approaches are commonly applied in delivery failure

prediction, demand forecasting, and operational logistics.

V. Hybrid Models Combining Multiple

risk prediction problems. Algorithms such as Logistic Regression, Decision Tree, and Random Forest are used to classify deliveries into low-risk and high-risk categories. Logistic Regression provides a simple and interpretable baseline model for binary delivery risk prediction. Decision Trees capture nonlinear relationships between delivery factors and outcomes; Computational complexity may increase when

Techniques

Hybrid models in intelligent delivery systems combine machine learning–based risk prediction with route optimization techniques to improve delivery performance and reliability. In this approach, supervised machine learning models such as Logistic Regression, Decision Tree, and Random Forest are used to predict delivery failure risk based on historical and operational delivery data. The predicted risk values are then integrated with optimization algorithms to support informed routing decisions.

Hybrid models offer improved accuracy, flexibility, and practical decision support in last-mile delivery operations. However, they introduce increased computational complexity and require well-structured datasets for effective performance. Despite these challenges, such hybrid approaches have proven effective in delivery risk management, adaptive route planning, and improving overall logistics efficiency in real-world delivery systems.

VI. Route Analysis and Delivery system Modeling

Route analysis and delivery system modelling play a fundamental role in understanding and improving last-mile parcel delivery performance. Route analysis evaluates delivery paths based on factors such as travel distance, delivery sequence, time constraints, and predicted delivery risk. Delivery system modelling focuses on how parcels are scheduled, routed, and delivered from local hubs to customers, considering operational constraints and delivery priorities.

optimizing routes for multiple deliveries with varying constraints. Despite these challenges, route analysis and delivery modelling have been successfully applied in delivery scheduling, delay reduction, and adaptive route planning for last-mile logistics.

Delivery optimization approaches have evolved from basic rule-based routing to intelligent machine learning and hybrid frameworks. While traditional ML models offer interpretability

VII. Advantages and Limitations of Various

A. Random Forest (RF)

Advantages : Robust, handles noisy data, provides feature and efficiency for delivery risk prediction, hybrid models that integrate risk prediction with route optimization provide improved delivery reliability. Future research should focus on enhancing real-time adaptability, improving model efficiency, and integrating delivery risk analysis more closely with route optimization to further improve last-mile delivery performance.

These modelling techniques enable the identification of inefficient routes and high-risk delivery locations, supporting optimized delivery planning. However, their effectiveness depends on the availability and accuracy of delivery-related data, such as historical delivery outcomes and location information.

importance.

Limitations: Limited to structured data, increased computational cost compared to single models

B. Logistic Regression

Advantages: Simple and interpretable, efficient for binary delivery risk prediction, low computational cost.

Limitations: Limited ability to capture complex non-linear relationships in delivery data.

C. Decision Tree

Advantages: Easy to understand and visualize, handles both numerical and categorical delivery attributes.

Limitations: Prone to overfitting, less robust when data contains noise.

D. Genetic Algorithm (GA)

Advantages: Effective for route optimization, handles multiple delivery constraints such as distance, time, and risk. **Limitations**: computationally expensive, requires high-quality input data.

E. Hybrid Models (ML + Route Optimization)

Advantages: Integrates delivery risk prediction with adaptive routing, improves delivery reliability and decision-making.

Limitations: Higher system complexity and implement, computational overhead during optimization.

TABLE I: Comparison of Different Smart Parcel Delivery Techniques

Technique	Strengths	Weaknesses	Performance Metrics	Applications
Traditional Route Planning (Google Maps / Static Shortest Path)	Simple and fast routing, widely used, easy integration.	Doesn't consider delivery risk factors like traffic, weather, theft zones, or failed delivery probability.	ETA Accuracy: Medium, Risk Handling: Low	Basic last-mile delivery planning, normal courier routing.
Rule-Based Risk Detection	Easy to implement, works with predefined conditions (if-else).	Not scalable, cannot learn from new patterns, low accuracy in real-time conditions.	Risk Prediction Accuracy: Low–Medium	Simple delivery risk alerts, manual monitoring systems.
Machine Learning Risk Prediction (Random Forest / XGBoost)	Predicts delivery failure risk using real-world features like delay, traffic, customer availability, area risk.	Needs quality dataset, model retraining required for new cities.	Risk Accuracy: High, Failure Prediction: Better than manual	Delivery failure prediction, risk based decision support.
Genetic Algorithm (GA) Based Route Optimization	Finds near-optimal routes, reduces delivery time and fuel cost, handles multiple constraints.	Computation cost increases with large delivery locations.	Route Cost Reduction: High, Optimization Score: Strong	Adaptive route planning for multi-stop parcel delivery.

VIII. Discussion on Real-World Applicability

A. Last-Mile Parcel Delivery Optimization

Machine learning–based delivery risk prediction models combined with route optimization techniques have strong applicability in real-world last-mile logistics operations. Predictive models such as Logistic Regression, Decision Trees, and Random Forest can be used to identify high-risk deliveries based on factors like customer availability, traffic conditions, and delivery time windows. These predictions help logistics managers proactively plan delivery schedules and reduce failed delivery attempts.

B. Delivery Risk Prediction in Data-Scarce Environments

Machine learning–based delivery risk prediction models can also be applied effectively in scenarios where historical delivery data is limited. Simple yet robust models such as Logistic Regression and Decision Trees can learn meaningful patterns from small datasets by leveraging key delivery attributes like distance, delivery time slots, and basic customer availability indicators.

C. Real-Time Delivery Risk Monitoring and Route Adaptation

Hybrid models that integrate machine learning–based delivery risk prediction with route optimization techniques support Realtime monitoring of delivery operations. By continuously evaluating delivery attributes such as traffic conditions, delivery progress, and time window constraints, these systems can dynamically update risk levels during ongoing delivery schedules.

D. Adaptation to Dynamic Operational Conditions Adapting delivery systems to changing operational conditions is essential for long-term efficiency and reliability in logistics networks. Factors such as increasing order volumes, urban traffic growth, changing customer behaviour, and time-based delivery constraints significantly influence delivery performance.

E. Policy and Decision-Making in logistics

The Data-driven delivery risk prediction and route optimization systems provide actionable insights for logistics planners and operational decision-makers. By identifying high-risk delivery zones, time windows with frequent failures, and inefficient routing patterns, such systems help organizations prioritize operational improvements and resource allocation.

IX. Current Limitations in the Field

A. Real-Time Data Integration

Machine learning–based delivery risk prediction models have demonstrated effectiveness in identifying potential delivery failures using historical delivery data. However, integrating real-time delivery data such as live traffic conditions, delivery progress updates, and dynamic customer availability remains a significant challenge. Delays in data updates or incomplete real-time information can reduce the accuracy of risk predictions during active delivery operations.

B. User-Friendly Applications

Many delivery risk prediction and route optimization models remain confined to analytical or experimental environments and lack user-friendly interfaces for practical use. The absence of intuitive platforms makes it difficult for delivery managers and operators to interpret risk predictions and optimize routes effectively. Without clear visualization and interaction, the adoption of intelligent delivery systems in real-world operations is limited.

C. Data Scarcity and Quality

High-quality and well-structured delivery data is essential for accurate delivery risk prediction and route optimization. Factors such as incomplete address information, missing delivery status updates, inconsistent time records, and limited historical delivery data can significantly affect model performance.

D. Model Generalization

Delivery risk prediction models trained on specific urban regions often struggle to generalize across different delivery environments. For example, a model trained on dense city deliveries may perform poorly in semi-urban or rural areas due to variations in distance, traffic, and customer availability. This highlights the need for transferable delivery risk prediction frameworks applicable across diverse logistics regions.

E. Computational Complexity

Machine learning models such as Random Forest and optimization techniques like Genetic Algorithms require significant computational resources as delivery volume increases. This can make real-time delivery risk prediction and adaptive route optimization challenging, especially in largescale or resource-constrained delivery operations.

X. Potential Research Opportunities

A. Real-Time Delivery Monitoring Applications Developing real-time web-based applications for delivery risk prediction and route visualization can bridge the gap between analytical models and real-world deployment. Features such as delivery risk dashboards and route tracking can improve operational usability.

B. Adaptive Route Optimization

Further research can explore dynamic route optimization that continuously updates delivery routes based on predicted risk levels. Integrating delivery risk prediction with adaptive Genetic Algorithm–based routing can enhance real-time **delivery** efficiency.

C. Explainable Delivery Risk Prediction

Improving model interpretability through explainable machine learning techniques can increase trust and adoption among delivery managers. Visualizing key delivery risk factors such as distance, time window, and location improves decision-making.

D. Scalable Delivery Risk Frameworks

Developing scalable delivery risk prediction frameworks that perform efficiently across varying delivery volumes and regions remains an important research direction. Such frameworks can support deployment in both urban and semiurban delivery environments.

E. Decision- Support Systems for Logistics

Integrating delivery risk insights into decision-support systems can assist logistics planners in optimizing scheduling, workforce allocation, and service-level strategies based on predicted delivery outcomes.

XI. EMERGING TECHNOLOGIES THAT COULD IMPROVE EXISTING METHODS

A. Real-Time Web-Based Processing

Deploying delivery risk prediction and route optimization models within web-based platforms enables near real-time decision-making. Lightweight ML models integrated into delivery management applications can process incoming delivery data quickly, reducing response time for route adjustments and delivery rescheduling. *B. Advanced Optimization Techniques*

Enhancements in evolutionary optimization techniques, such as improved Genetic Algorithm variants, can further optimize delivery routing under dynamic constraints. These techniques can handle multiple objectives, including minimizing delivery time, reducing risk, and balancing delivery workload.

C. Secure Data Handling and Transparency

Improving data handling mechanisms ensures reliable and consistent delivery risk prediction. Structured data storage and secure data flow between prediction models and delivery applications help maintain data integrity, especially in multilocation logistics operations. *D. Intelligent Decision-Support Systems*

Integrating machine learning–based risk prediction with decision-support modules can enhance delivery planning and monitoring. Such systems can provide actionable insights through dashboards, enabling delivery managers to make informed routing and scheduling decisions efficiently.

XII. Real-Time Applications and Practical Implementation Issues

A. Real-Time Delivery Monitoring and Visualization

A web-based application can be used to monitor delivery status, predicted risk levels, and optimized routes in real time. Challenges include delayed delivery updates and system response time.

B. Delivery Alerts and Decision Support

Early alert mechanisms help delivery managers respond to high-risk deliveries. Issues such as inaccurate predictions and false alerts must be minimized. Issues such as inaccurate predictions and false alerts must be minimized.

C. Scalability and Accessibility

Scaling the system to handle large delivery volumes while maintaining prediction accuracy is challenging. Ensuring accessibility for smaller logistics operations is also important.

D. Operational and Management Challenges

Real-world deployment requires coordination between technical systems and delivery operations. Data sharing and system integration remain key challenges.

XIII. Summary of Key Findings

- This survey paper examined the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques for delivery failure risk prediction and adaptive route optimization in last-mile logistics systems. The key findings are summarized as follows:

  Machine Learning models, particularly Random Forest and Decision Tree classifiers, were found to be effective in predicting delivery failure risks by analysing historical delivery patterns, traffic conditions, and customer-related factors. Their ability to handle complex, multidimensional delivery data makes them suitable for logistics risk assessment.

  Optimization techniques, such as Genetic Algorithms, demonstrated strong potential in generating efficient delivery routes by minimizing travel distance, delivery time, and failure probability. These algorithms are especially effective in handling dynamic delivery constraints and multi-stop routing scenarios.
- **Integrated risk-aware delivery frameworks** bridge the gap between predictive analytics and real-world delivery execution by combining risk prediction with adaptive route planning, enabling proactive decision-making and improved delivery reliability.
- **Decision support systems and interactive dashboards** enhance usability by allowing logistics managers to visualize delivery risk levels, optimized routes, and operational insights, thereby improving planning efficiency and response to high-risk delivery situations. The survey also highlights the importance of incorporating real-time operational factors, such as traffic congestion and customer availability, to improve prediction accuracy and support scalable, intelligent logistics solutions.

XIV. Final Thoughts on Advancements in the Field

The field of intelligent logistics and last-mile delivery have witnessed notable advancements in recent years, driven by the adoption of Artificial Intelligence (AI), Machine Learning (ML), and optimization techniques. These advancements have enabled improved delivery risk prediction, efficient route planning, and data-driven decision-making in complex delivery environments. AI-based models have demonstrated strong potential in addressing key challenges such as delivery delays, failures, traffic congestion, and operational inefficiencies. However, issues related to data availability, real-time adaptability, and scalability continue to pose challenges for widespread deployment.

The development of integrated risk-aware delivery frameworks represents a significant step forward in overcoming these limitations by combining predictive analytics with adaptive route optimization. By leveraging ML-based risk assessment and intelligent routing strategies, such systems enhance delivery reliability, reduce operational cost, and support proactive logistics management.

XV. Future Perspectives and Possible Research Directions

a. Enhancing Real-Time Capabilities

Future research should focus on improving the real-time adaptability of delivery risk prediction systems by integrating live traffic data, GPS-based vehicle tracking, and streaming delivery updates. This would enable dynamic route adjustments and more accurate delivery risk assessment during active delivery operations.

b. Explainable AI (XAI) for Logistics Decision-Making

The development of explainable AI (XAI) techniques for delivery risk prediction models can enhance transparency and trust among logistics managers and delivery agents. Visual explanations such as feature importance and risk factor breakdowns can support informed and confident decision making.

c. Integration of Environmental and Temporal Factors

Incorporating environmental conditions such as weather patterns, peak-hour congestion, and seasonal demand variations can improve delivery risk prediction accuracy. Future studies should explore how these factors influence delivery outcomes and integrate them into real-time routing systems.

d. Scalable and Transferable Delivery Models

Designing scalable and transferable delivery prediction models that can be applied across different cities and delivery networks is a key research direction. Pre-trained models can be fine-tuned for new regions or logistics providers with minimal data, improving adaptability and deployment efficiency.

e. User-Friendly Decision Support Applications

Future work should emphasize the development of intuitive and user-friendly decision support tools for logistics managers and delivery coordinators. Interactive dashboards and visualization interfaces can simplify delivery planning and enhance operational efficiency.

f. Integration of Customer Behaviour and Socioeconomic Factors

Incorporating customer behaviour patterns, location characteristics, and socioeconomic indicators can help identify high-risk delivery zones and improve delivery success rates.

g. *Scalable Logistics Analytics*

Studying scalable analytics frameworks that can handle large volumes of delivery data while maintaining prediction accuracy and responsiveness remains a key research opportunity.

XVI. Closing Remarks

The integration of Machine Learning–based risk prediction and adaptive route optimization has the potential to significantly enhance last-mile parcel delivery efficiency and reliability. By addressing challenges such as delivery failures, delays, and inefficient routing, our project supports data-driven decision making and helps reduce operational costs. Our project provides a practical approach to smarter and more responsive delivery management by enabling effective planning and execution. As logistics systems continue to evolve, our project contributes toward building efficient and sustainable solutions for modern delivery networks.

References

[1] Kumar, R., Singh, S. P., & Shankar, R. (2025). Machine learning–based prediction of delivery failures in last-mile logistics systems. *International Journal of Intelligent Transportation Systems Research*. https://doi.org/10.1007/s13177-025-00345-2

[2] Zhang, Y., Liu, X., & Wang, H. (2025). Intelligent route optimization for urban parcel delivery using evolutionary algorithms. *IEEE Transactions on Intelligent Transportation Systems*. https://doi.org/10.1109/TITS.2025.3349123

[3] Li, J., Chen, M., & Zhao, Y. (2024). Risk-aware parcel delivery optimization using machine learning and realtime traffic data. *Transportation Research Part E: Logistics and Transportation Review*. https://doi.org/10.1016/j.tre.2024.102567

[4] IEEE Xplore. (2024). Optimized parcel delivery and pickup scheduling using evolutionary genetic algorithms. *IEEE International Conference on Smart Logistics*. https://ieeexplore.ieee.org/document/11122443

[5] Wang, S., Ma, X., & Liu, Y. (2024). Predicting delivery delays in e-commerce logistics using ensemble learning models. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2024.121034

[6] Amazon Web Services. (2023). Last-mile delivery optimization using machine learning. *AWS Whitepaper*. https://aws.amazon.com/solutions/implementations/lastmile-delivery-optimization/

[7] Chen, Q., Sun, Z., & Li, R. (2023). A data-driven framework for delivery time prediction in large-scale logistics networks. *Computers & Industrial Engineering*. https://doi.org/10.1016/j.cie.2023.109120

[8] Liu, H., Zhang, D., & Xiong, J. (2023). Genetic algorithm–based route planning for smart logistics applications. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2023.137845

[9] Zhao, P., He, Z., & Xu, C. (2022). Intelligent decision support systems for last-mile delivery management. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2022.103746

[10] Scikit-learn Documentation. (2022). Machine learning algorithms for classification and prediction. https://scikit-learn.org

[11] Ulmer, M. W., Goodson, J. C., & Thomas, B. W. (2021). Dynamic routing for last-mile delivery considering uncertainty. *Transportation Science*. https://doi.org/10.1287/trsc.2021.1065

[12] Boysen, N., Fedtke, S., & Schwerdfeger, S. (2020). Lastmile delivery concepts: A survey from an operations research perspective. *OR Spectrum*. https://doi.org/10.1007/s00291-020-00587-0