Literature Map & Bibliography

Topic: *AI-Driven Route Optimization and Delay Prediction System for Fleet Operations*

1. **Foundations of Dynamic & Stochastic Routing**
    - Dynamic vehicle routing problems: Three decades and counting by H. N. Psaraftis et al. (2016) provides a survey of Dynamic Vehicle Routing Problems (DVRP).
    - A stochastic and dynamic vehicle routing problem in the Euclidean plane by D. J. Bertsimas & G. van Ryzin (1991) establishes early stochastic and dynamic VRP formulations.
2. **Data Foundations for AI Modelling**
    - Last-mile delivery route deviations dataset: planned vs. actual routes (Konovalenko, Hvattum, Iversen, 2024) gives real-world last-mile delivery route data (planned vs actual) across two countries, with time windows, driver IDs, stop sequences, etc.
    - LaDe: The First Comprehensive Last-mile Delivery Dataset from Industry (Wu et al., 2023) offers large-scale industry last-mile delivery data useful for model training/validation.
3. **AI and Reinforcement Learning for Route Optimization**
    - Reinforcement learning-based routing optimization in dynamic logistics networks by Y. Gao, J. Tang & X. Liu (2022) illustrates how RL can optimize routing under dynamic conditions.
4. **Deep Learning for Delivery Delay Prediction**
    - A deep learning approach to predict supply chain delivery delay risk based on macroeconomic indicators: a case study by M. Gabellini et al. (2024) uses deep learning to predict delay risk in supply chains.
    - DeepSTA: A Spatial-Temporal Attention Network for Logistics Delivery Timely Rate Prediction in Anomaly Conditions (Yi et al., 2025) explores advanced spatial-temporal attention networks for predicting delivery timely rates under anomalous conditions.
5. **Integration & Research Gap**
    - The path traced by these works moves from classical dynamic routing theory → data for modelling real-world deviations → AI/ML for optimization and prediction.
    - The remaining gap: **a unified system** that combines *real-time route re-optimization* (using RL or similar) with *delay prediction* (using deep/spatio-temporal models) and uses real-world deviation datasets (such as the Mendeley dataset) in large-scale fleet operations.

Bibliography

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3. Konovalenko, A., Hvattum, L. M., & Iversen, K. A. H. (2024). *Last-mile delivery route deviations dataset: planned vs. actual routes.* Version 1. DOI: 10.17632/kkwgfvmtxn.1. Mendeley Data
4. Wu, L., Wen, H., Hu, H., Mao, X., Xia, Y., Shan, E., … Wan, H. (2023). *LaDe: The First Comprehensive Last-mile Delivery Dataset from Industry.* arXiv preprint arXiv:2301.09123. arXiv
5. Gao, Y., Tang, J., & Liu, X. (2022). *Reinforcement learning-based routing optimization in dynamic logistics networks.* IEEE Transactions on Intelligent Transportation Systems. ResearchGate
6. Gabellini, M., Civolani, L., Calabrese, F., & Bortolini, M. (2024). *A deep learning approach to predict supply chain delivery delay risk based on macroeconomic indicators: a case study.* Applied Sciences, 14(11), 4688. MDPI