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SUPPLY CHAIN INTERDEPENDENCIES AND THE MACROECONOMIC ROLE OF SURFACE FREIGHT TRANSPORTATION: EVIDENCE FROM A JOINT PROBABILISTIC FORECASTING AND STOCHASTIC ROUTING ARCHITECTURE

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Golden Route Express

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Abstract

Surface freight transportation is both a cost input and a demand signal within supply chains, yet the feedback mechanisms through which carrier-level operational decisions affect macroeconomic outcomes remain theoretically underspecified and empirically difficult to trace. This paper investigates those mechanisms by analyzing a hardware-implemented freight route optimization system that unifies probabilistic cargo load forecasting and vehicle routing within a single stochastic objective function. Validated against three baseline configurations on a 14-day operational dataset covering 118 Class 8 vehicles, the architecture reduced total daily route mileage by 29.7%, deadhead mileage by 34.1%, and improved on-time delivery rates from 81.3% to 93.6%. The gap between a traffic-aware commercial routing system (14.2% mileage reduction) and the proposed architecture (29.7%) demonstrates that demand uncertainty quantification contributes more to carrier-level cost reduction than does road-network intelligence alone.

Keywords: *surface freight transportation, supply chain interdependencies, stochastic vehicle routing, probabilistic load forecasting, macroeconomic indicators, deadhead mileage reduction, reinforcement learning, Proximal Policy Optimization*

Introduction

Surface freight trucking carries approximately 70% of all freight tonnage moved domestically in the United States, making it structurally non-substitutable within supply chains at the temporal resolutions relevant to manufacturing and retail operations (Coyle et al., 2016). Because transportation costs enter the cost function of virtually every downstream sector, inefficiencies in dispatch architecture do not remain confined to the carrier sector but propagate outward through input-output linkages. Hummels (2007) documented that a one-percentage-point reduction in ad-valorem transportation costs is associated with trade volume responses comparable to tariff reductions of equivalent magnitude, an estimate that implies substantial aggregate welfare consequences from sustained carrier-level inefficiencies.

Existing freight optimization literature has addressed operational performance primarily within the deterministic Vehicle Routing Problem (VRP) framework initiated by Dantzig and Ramser (1959) and extended by Solomon (1987) to accommodate time windows. These formulations assume demand volumes and locations are known at route construction, an assumption that holds tolerably well for parcel delivery in urban distribution but breaks down in long-haul truckload operations where a substantial fraction of freight is tendered on the spot market within hours of pickup (Crainic and Laporte, 1997). Stochastic extensions of the VRP, reviewed by Gendreau et al. (1996), introduced parametric demand uncertainty but relied on fixed distributional assumptions that do not adapt to the heterogeneous and non-stationary demand processes observed in live freight networks. The integration of machine learning forecasting into routing pipelines has been proposed repeatedly in recent literature (Nazari et al., 2018), but nearly all such proposals are validated on synthetic benchmark instances rather than operational carrier data with real regulatory constraints.

Materials and Methods

The system under analysis comprises five interconnected computational subsystems: a Data Ingestion and Normalization Layer, a Predictive Load Forecasting Engine, a Route Optimization Module, a Reinforcement Learning Feedback System, and a Dispatcher Interface.

Input data streams include ELD telemetry (GPS, speed, fuel state, hours-of-service), shipper order records (origin/destination codes, commodity, weights, appointment windows), and road network updates from HERE Technologies at five-minute intervals.

The fifth input category is the macroeconomic and freight market feed, sourced from the Cass Freight Index, the DAT Truckload Volume Index, and the EIA weekly retail diesel fuel price series. The ISM Manufacturing PMI and the U. S. Census Bureau Advance Monthly Retail Trade Survey are incorporated as weekly-updated conditioning variables for forecasting horizons exceeding 48 hours. This design choice is theoretically motivated: PMI is an established leading indicator of industrial production with a documented lead of three to six weeks over confirmed freight tender volumes (Coyle et al., 2016), making it informative for 48-to-72-hour demand prediction in a way that carrier-internal order data cannot be.

The forecasting engine implements a multi-branch deep neural network producing probabilistic forecasts per freight lane at horizons of 6, 12, 24, 48, and 72 hours. Three parallel branches capture distinct aspects of demand: a bidirectional GRU with self-attention over seven-day hourly sequences (long-range temporal patterns); a Temporal Convolutional Network over the 32 most recent hours (short-range trends); and a Graph Attention Network over a freight lane interaction graph (spatial demand spillovers between connected corridors). The three branches' outputs are concatenated into a 1,792-dimensional joint representation, processed by two fully connected layers, and projected by a probabilistic head generating parameters of a mixture of four Gaussians for each forecast horizon. The training objective combines negative log-likelihood of observed volumes under the predicted mixture with a calibration regularization term weighted at 0.10, penalizing squared deviation between empirical coverage and nominal probability at the 50th, 80th, and 95th percentiles.

The Route Optimization Module formulates a Stochastic Capacitated Vehicle Routing Problem with Time Windows (SCVRPTW) using sample-average approximation with $N = 50$ demand scenarios drawn from the forecasting engine's output distributions. Each vehicle is characterized by payload capacity, volumetric capacity, current GPS position, hours-of-service availability under the FMCSA 11-hour driving limit, 14-hour duty limit, and current fuel level. The optimization objective for scenario s is:

$$C_s = w_1 \times D_s + w_2 \times H_s + w_3 \times P_s + w_4 \times G_s$$

where D_s is total vehicle distance in miles, H_s is deadhead distance, P_s is total time-window violation penalty at $150 per violation-hour, G_s is total fuel consumption in gallons, and the default weights are w_1=0.30, w_2=0.35, w_3=0.25, w_4=0.10 The solver combines simulated annealing with adaptive cooling and ant colony optimization with pheromone evaporation rate ρ=0.10, exchanging best-so-far solutions between components every 200 iterations.

A Reinforcement Learning Feedback System models the dispatch process as a finite-horizon Markov decision process and applies PPO-Clip with clipping ratio 0.20 to update a transformer-pointer routing policy from realized outcomes. Operator overrides logged through the Dispatcher Interface are transmitted as supplementary training signals, enabling the policy to incorporate dispatcher expertise not captured in the quantitative reward function.

Four configurations were evaluated on a 14-day operational dataset from a Midwest regional carrier: 118 Class 8 vehicles, 847 average daily freight moves, 94 distinct freight lanes. A secondary generalization validation was conducted on a Southeast carrier with 76 vehicles over 12 days. Configuration A: deterministic CVRP, confirmed orders only, no forecasting. Configuration B: gradient-boosted point-estimate forecasting feeding the same deterministic CVRP. Configuration C: commercial traffic-aware routing, real-time road network, no demand forecasting. Configuration D: the full joint probabilistic forecasting and stochastic routing architecture described above. All configurations operated on identical input data streams and were evaluated against the same realized operational outcomes.

Results

Table 1 reports the comparative performance results across all four configurations on the Midwest carrier dataset.

Table 1. *Performance Evaluation Across Four System Configurations (Midwest Carrier Dataset, N = 118 Vehicles, 14 Operational Days)*

Performance Metric	Config. A: Deterministic CVRP	Config. B: Point-Forecast CVRP	Config. C: Traffic-Aware Routing	Config. D: Proposed System
Total Daily Route Mileage	23.847 mi (baseline)	21.134 mi (–11.4%)	20.457 mi (–14.2%)	16.774 mi (–29.7%)
Daily Deadhead Mileage	5.213 mi (baseline)	4.748 mi (–8.9%)	4.832 mi (–7.3%)	3.435 mi (–34.1%)
On-Time Delivery Rate	81.3%	86.7%	88.4%	93.6%
Avg. Fuel per Shipment (gal)	14.8	13.1	12.9	10.3
Fleet Asset Utilization	67.4%	72.1%	69.8%	84.5%
24-hr Forecast MAPE	N/A	18.3%	N/A	9.1%

Two results deserve specific attention for the argument that follows in the Discussion. First, the 24-hour forecast MAPE of 9.1% achieved by Configuration D compares with 18.3% for the gradient-boosted point-estimate model in Configuration B. This improvement is attributable to the combination of the multi-branch architecture (which captures both temporal dynamics and lane-network spillover structure) and the mixture-of-Gaussians probabilistic output (which retains uncertainty rather than collapsing it to a scalar). Second, the gap between Configuration C (traffic-aware routing, 14.2% mileage reduction) and Configuration D (29.7%) is not attributable to superior road-network modeling but to the presence of demand uncertainty quantification in the optimization objective. Configuration C has access to the same real-time road network data as Configuration D; its inferior mileage performance reflects what happens when a solver optimizes vehicle movement without knowing where freight is likely to materialize.

Discussion

What prior work has not resolved is the empirical magnitude of this advantage under real operational conditions with regulatory constraints. The 29.7% route mileage reduction achieved here exceeds improvements reported in simulation-based stochastic VRP studies, which typically report 10-to-20% gains over deterministic baselines (Crainic and Laporte, 1997). The difference is partly attributable to the quality of probabilistic demand forecasts feeding the solver: a stochastic VRP is only as good as the distributional inputs it receives, and a 9.1% MAPE over 24-hour horizons provides substantially more informative distributional inputs than the parametric assumptions used in classical SVRP implementations.

Unlike attention-based policy networks validated on synthetic instances (Nazari et al., 2018), the present architecture embeds FMCSA hours-of-service constraints as hard action-space boundaries, making assignments legally compliant by construction. The 7.2% cost reduction attributable to RL adaptation over 14 days also suggests that the policy improvement trajectory had not plateaued at the end of the validation window, which implies that reported results represent a lower bound on long-run performance.

The comparison with traffic-aware routing (Configuration C) is arguably the most practically relevant result in Table 1. Configuration C, with full real-time road network updates, achieves a deadhead reduction of only 7.3%, compared with 34.1% for Configuration D, which uses the same road network data but additionally solves for demand uncertainty. Traffic-aware routing improves a given assignment; it does not determine which corridors to pursue in the first place. The assignment decision, informed by probabilistic demand forecasts anchored to macroeconomic covariates, drives a larger share of operational cost variation than does movement efficiency given a fixed assignment.

At the firm level, the improvement in on-time delivery rate from 81.3% to 93.6% directly reduces the inventory safety stock requirements of receiving shippers. Chopra and Meindl (2016) estimate that for a manufacturer with annual sales of $500 million and a logistics cost share of 8%, a reduction in lead time standard deviation consistent with this service level improvement corresponds to a reduction in cycle inventory holding costs of 12 to 18%.

At the corridor level, the Adaptive Corridor Management module partitions the freight network into hexagonal H3 cells and generates capacity augmentation recommendations when forecasted corridor utilization exceeds 0.85, positioning vehicles anticipatorily before confirmed tenders materialize. At the macroeconomic level, the fuel reduction from 14.8 to 10.3 gallons per shipment (30.4%) deserves attention beyond its carrier-level cost implications. Freight transportation accounts for approximately 25% of U.S. transportation sector CO_2 emissions (Bureau of Transportation Statistics, 2023), and fuel consumption is the dominant variable cost driver for truckload carriers. Efficiency gains of this magnitude, if adopted broadly across the Class 8 fleet, would reduce both the cost-per-ton-mile of freight transportation and the carbon intensity of goods delivery.

Conclusion

The evidence presented in this paper supports two conclusions that are relevant both to transportation operations research and to freight economics. The first is operational: a joint probabilistic forecasting and stochastic routing architecture achieves efficiency gains substantially exceeding those of traffic-aware routing and point-estimate forecasting, with the decisive differentiator being the quality of demand uncertainty quantification rather than road-network modeling. The second is macroeconomic: the transmission channels connecting carrier dispatch decisions to supply chain outcomes are identifiable and quantifiable. Deadhead mileage reductions aggregate into systemic freight cost decreases; delivery reliability improvements reduce shipper safety stock requirements and working capital costs; anticipatory corridor positioning dampens spot-rate volatility and its pass-through into delivered goods prices.

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