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Research on Multi-modal Transportation Decision-making and Risk Control Strategies under Time-sensitivity Constraints

Zinuo Tao *

School of Management, Shandong University, Jinan, Shandong, 250100, China

**Corresponding author: Zinuo Tao*

Abstract

This paper investigates the conflict between consumer demands for prompt delivery and the uncertainty of actual transit times in the e-commerce era. A novel cost optimization model is proposed that integrates transportation costs and penalty costs, aiming to optimize transportation mode selection while minimizing both explicit and implicit costs. By analyzing historical order data, the study fits the actual transit times for various transportation modes into normal distribution functions. Utilizing the Sample Average Approximation (SAA) method, the expected objective function is modeled in Python and solved using the Gurobi optimizer to determine the recommended transportation modes and associated costs. A comparison between actual costs and model-derived results indicates that the proposed model significantly reduces penalty costs and lowers total operational costs. Consequently, this approach safeguards corporate goodwill and mitigates intangible losses that are otherwise difficult to quantify. The findings suggest that enterprises should look beyond standalone transportation expenses and adopt a comprehensive cost model that incorporates penalty-based risk factors.

Keywords

time-sensitive issues, multi-modal transportation, penalty costs, risk control

1. Introduction

With the rapid proliferation of e-commerce, online shopping has become a primary consumer behavior. While offering diverse product selections, online platforms often face significantly lower delivery timeliness compared to traditional offline retail. Consequently, the precision and efficiency of delivery have emerged as critical determinants of consumer preference, serving as a core performance metric for logistics providers.

To address varied consumer expectations, enterprises frequently employ multi-modal transportation strategies to offer tiered services, such as “same-day” or “next-day” delivery. Traditionally, transportation mode selection is driven primarily by cost-minimization. However, transit times are inherently susceptible to stochastic uncertainties—such as adverse weather and traffic congestion—leading to significant fluctuations. These temporal variations are widely characterized as following a normal distribution in existing literature [1]. Such discrepancies between planned and actual arrival times often result in delivery delays, triggering late-delivery penalties and causing intangible damage to corporate goodwill.

Given these challenges, cost structures in logistics must evolve beyond direct transportation expenses to incorporate the financial risks of non-compliance with delivery windows. This study develops a stochastic optimization model that integrates both transportation and penalty costs. By factoring in the costs of breach of timeliness, this research provides a theoretical framework and practical guidance for enterprise decision-making within uncertain transportation environments.

2. Literature Review

The multimodal transportation route optimization problem has long been a topic of widespread attention in academia. This study focuses on the inherent tension between timeliness commitments and transportation time uncertainty. Through research on multimodal transportation route optimization, transportation uncertainty modeling, and service fulfillment decisions under timeliness commitments, a theoretical model for solving this problem is derived.

2.1 Research on Multimodal Transportation Route Optimization

The issue of multimodal transportation has been studied for some time, with cost minimization or the shortest transportation time being the core objectives. SteadieSeifi conducted a systematic review of multimodal transport planning models and algorithms, pointing out that transportation cost, time, and reliability are the key trade-offs in route decisions. Early research typically assumed a deterministic environment, where overly idealized assumptions ignored the external factors affecting actual business operations. Factors such as diverse weather conditions and road congestion made many previous models incompatible with real-world situations, highlighting the need for more practical considerations [2].

2.2 Modeling Uncertainty in the Transportation Process

Stochastic programming methods describe uncertain parameters using known probability distributions. Cheng Xingqun et al. addressed the uncertainty in transportation time and unit freight rates in multimodal transportation by employing Box uncertainty sets to characterize these factors. They developed a robust multimodal transportation path optimization model with adjustable robustness [3]. Tong established a multimodal rail transport path optimization model under uncertain transportation time conditions [4].

2.3 Research on Timeliness Commitment and Fulfillment Decisions

Logistics services based on timeliness commitments have become a competitive focus. In transportation route decisions, network risks and other uncertainties must be quantified and incorporated into the objective function for integrated optimization. Pei Yingmei et al. constructed a multi-objective programming model that considers transportation network risks, costs, and time, aiming to find the optimal path to mitigate risks [5]. This paper draws on their research and incorporates the timeliness breach risk caused by transportation time uncertainty, represented by expected penalty costs in the model.

2.4 Literature Review and Research Positioning

Academic achievements have been made in multimodal transportation optimization, uncertainty modeling, and timeliness fulfillment. However, some research gaps still remain. Most studies either treat transportation time as a deterministic problem or, while considering its randomness, fail to integrate this randomness with specific timeliness commitments (T_i) and tiered penalty mechanisms (π_i) for enterprises.

Traditional cost minimization models often overlook implicit costs, focusing on reducing transportation costs while ignoring the significant expected penalty risks arising from transportation time uncertainty, thus failing to achieve optimal cost efficiency.

This study aims to fill these gaps by constructing a stochastic optimization model that integrates transportation time randomness and timeliness fulfillment penalties. It transforms macro-level uncertainties, such as weather and congestion, into relatively fixed and computable factors using probability distributions and expected penalty functions, offering new cost calculation approaches for logistics companies.

3. Model Construction

This paper constructs a stochastic optimization model for multimodal transportation path decision-making, applicable to third-party logistics companies. It quantifies the delivery delays caused by transportation time uncertainty as an expected penalty cost, and integrates this with the traditional transportation costs into the decision-making objective, ensuring both cost and service guarantees.

3.1 Problem Description and Key Assumptions

The model is set within the context of a third-party logistics company facing multimodal transportation decision-making scenarios. The network consists of nodes (such as cities, hubs) and directed arcs representing transportation segments. Each order i is defined by its origin, destination, cargo volume, and committed delivery timeliness T_i, and is associated with a fixed freight revenue R_i. Given that the revenue is fixed, the decision objective focuses on cost minimization. The company needs to assign an appropriate transportation path to each order from a set of feasible paths composed of various transportation modes.

To build a rigorous mathematical model, the following key assumptions are proposed in this study:

1. The logistics transportation network is known and fixed, consisting of a set of nodes and directed arcs.

2. The unit transportation cost c_a for using a specific transportation mode m_a on each transportation segment a is fixed and known.

3. The transportation time L_a for each transportation segment a is a continuous random variable, whose probability distribution $F_a(\cdot)$ can be estimated from historical data. The transportation times for different segments are independent of each other.

4. The origin and destination, cargo specifications, and corresponding freight revenue R_i for all customer orders are known prior to decision-making.

5. If the actual delivery time of order i exceeds the committed time T_i , a penalty cost, proportional to the delay duration, is incurred. The unit penalty rate is π_i

6. The total available capacity Cap_a for each transportation segment a during the planning period is limited.

3.2 Notation

For clarity, the mathematical symbols used in the model are explained as follows:

Sets:

I: Set of orders, $i \in I$

A: Set of transportation segments (arcs), $a \in A$

P_i: Set of feasible paths for transporting order i, $p \in P_i$

Parameters:

T_i: Delivery deadline for order i

π_i: Unit delay penalty cost for order i per time unit

c_a: Unit transportation cost for transportation segment a

Cap_a: Total available capacity for transportation segment a

δ_{ap}: Binary indicator, δ_{ap} =1 if path p includes arc a, and 0 otherwise

$L_p = \Sigma_a \in pL_a$: Total random transportation time for path p

$f_p(\cdot), F_p(\cdot)$: Probability density function and cumulative distribution function of the total transportation time L_p for path p

Decision Variables:

$x_i p \in \{0,1\}$: Binary decision variable, equal to 1 if order i selects path p, otherwise 0

3.3 Stochastic Programming Model

Based on the above problem description and assumptions, the core of this study is to construct a stochastic programming model that minimizes the expected total cost. The total cost of the model consists of two parts: (1) the deterministic transportation cost, and (2) the expected penalty cost caused by uncertain transportation times.

3.3.1 Objective Function

The objective function is as follows:

$$Min\Sigma_i\Sigma_p[c_p \cdot x_i p] + \Sigma_i\Sigma_p[E(\pi_i \cdot max(0, L_p - T_i)) \cdot x_i p]$$

Where:

The first term$\Sigma_i\Sigma_p c_p \cdot x_i p$ represents the total transportation cost, with $c_p = \Sigma_a \in pc_a$ being the fixed transportation cost for path p. The second term $\Sigma_i\Sigma_p E(\pi_i \cdot max(0, L_p - T_i)) \cdot x_i p$ represents the total expected penalty cost. This term quantifies the economic value of the potential breach risk caused by the random fluctuation in transportation time.

The expected penalty term $E(\pi_i \cdot max(0, L_p - T_i))$ can be further expanded as a probability integral based on the transportation time distribution for path p:

$$E(\pi_i \cdot max(0, L_p - T_i)) = \pi_i \cdot \int_{T_i}^{\infty}(l - T_i) f_p(l) dl$$

This integral calculates the weighted average of the penalty costs for all possible delay scenarios. By incorporating this risk cost into the objective function, the model allows for proactive avoidance of high-risk paths during the decision-making phase, thereby achieving preemptive risk control.

3.3.2 Constraints

The model must satisfy the following constraints:

(1) $\Sigma_p x_i p = 1, \forall i \in I$

This constraint ensures that each order is transported and assigned to exactly one path through the decision variable $x_i p$, guaranteeing that all orders are delivered.

(2) $\Sigma_i\Sigma_p \delta_a p \cdot x_i p \leq Cap_a, \forall a \in A$

This constraint ensures that the capacity on each transportation segment does not exceed its actual limit.

(3) $x_i p \in 0,1, \forall i \in I, p \in P_i$

This constraint defines the domain of the decision variable.

4. Solution Methodology and Experimental Analysis

4.1 Model Solution Based on Sample Average Approximation

To address the challenge of directly solving the expectation term in the objective function of the model, this paper employs the Sample Average Approximation (SAA) method. The relevant model is implemented in Python, where a set of randomly generated sample scenarios is used to simulate the uncertainty in transportation times, thereby transforming the complex stochastic programming model into a deterministic optimization problem.

The simulation is based on the transportation time distributions for each segment fitted using historical data. The model computes hundreds of possible future transportation scenarios, such as which routes might experience congestion and which trips could be delayed. These scenarios include the specific transportation times for all segments in the network. The SAA model is used to calculate the total transportation cost along with the average penalty cost under the simulated scenarios.

Using the large set of generated scenarios, the paper approximates the mathematical expectation, which was originally difficult to compute, by the simple arithmetic average of the penalty costs across these scenarios. As a result, the original stochastic model is converted into a deterministic mixed-integer linear programming (MILP) model of larger scale. The new model has a clear structure, and efficient solution is achieved using the Gurobi solver, which provides the final path allocation solution.

4.2 Experimental Design and Data Sources

To validate the effectiveness and superiority of the model, this study designs numerical experiments comparing the proposed SAA stochastic optimization model with historical strategies. The goal is to evaluate whether the transportation mode selection optimized by the model is superior to the actual historical situation.

The experimental data comes from 200 real historical order records from a third-party logistics company in China for the year 2023. These records cover intercity transportation in the East China, South China, and North China regions, ensuring both generality and authenticity. The transportation network includes three modes: road, rail, and air. The unit transportation costs are set based on market average prices. The 200 historical orders were analyzed and calculated to obtain the probability distribution parameters for the unit transportation time for each mode.

Road transportation: $L_a\ N(\mu = 0.20, \sigma = 0.05)$ days per 100 km

Rail transportation: $L_a\ N(\mu = 0.12, \sigma = 0.03)$ days per 100 km

Air transportation: $L_a\ N(\mu = 0.08, \sigma = 0.04)$ days per 100 km

4.3 Comparative Analysis

The historical actual total cost is calculated as:

Historical Total Cost=∑(actual transportation cost of each historical order+penalty cost calculated based on the actual delay days under the penalty rules)

The expected total cost under the proposed model is calculated as:

Expected Total Cost of the Model=∑(transportation cost of the path recommended by the model for each order+expected penalty cost)

As shown in Table 1, the changes in key performance indicators under different strategies can be computed, including total transportation cost, total penalty cost, total cost, average delivery delay, and timeliness fulfillment rate.

Table 1: Cost Comparison under Different Strategies

Cost Components and Performance Indicators	Historical Strategy	Model-Recommended Strategy	Improvement
Total transportation cost (10,000 CNY)	35.10	36.72	+4.6%
Total penalty cost (10,000 CNY)	7.02	4.05	-42.3%
Total cost (10,000 CNY)	42.12	40.77	-3.2%
Average delivery delay (days)	1.31	0.61	-53.4%
Timeliness fulfillment rate (%)	82.8%	91.7%	+8.9%

4.4 Results Analysis and Managerial Implications

The analysis of Table 1 shows that the proposed model achieves a substantial 42.3% reduction in penalty costs by accepting a 4.6% increase in transportation costs, while simultaneously lowering the overall total cost and significantly improving the timeliness fulfillment rate. This indicates that the model better satisfies consumers' delivery time expectations. The experimental results clearly demonstrate the importance of incorporating penalty costs into decision-making for reducing enterprises' implicit costs.Under the historical strategy, the exclusive pursuit of transportation cost minimization led to the neglect of potential penalty risks, resulting in a higher realized total cost.

The proposed model achieves a more precise trade-off between cost and risk by explicitly integrating penalty costs—previously overlooked—into the cost calculation framework, thereby mitigating implicit losses caused by delivery time violations.

Enterprises should move beyond the traditional practice of considering transportation costs alone and establish a new accounting framework based on “transportation cost + expected penalty cost”.

5. Conclusion

This study addresses the core conflict between timeliness commitments and transportation reliability in e-commerce logistics by investigating the multimodal transportation path optimization problem faced by third-party logistics providers. By developing a stochastic optimization model that explicitly incorporates transportation time reliability, this research provides both theoretical support and practical guidance for enterprises seeking to balance cost efficiency and service performance under uncertainty.

5.1 Research Summary

By constructing a stochastic optimization model with explicit timeliness constraints, this study overcomes a key limitation of prior research that neglected penalties arising from actual delivery delays. By incorporating delay penalty costs into the cost formulation, the proposed model extends traditional approaches that focus solely on transportation costs and offers new insights for transportation mode selection in logistics operations.

In the solution and empirical validation process, historical data on committed delivery times, actual delivery times, and delay durations were analyzed to estimate normal distributions for transportation times across different modes, characterized by parameters μ and σ. Using the Sample Average Approximation method, the theoretical model was implemented in Python and solved efficiently using the Gurobi optimizer. The resulting model outputs transportation recommendations under known transportation time distributions, achieving significant reductions in both penalty costs and total costs, while mitigating reputation losses for enterprises.

5.2 Theoretical Contributions and Managerial Implications

Incorporating penalty costs enables transportation mode selection models to better reflect real-world operational conditions, resulting in more accurate cost estimation. By reducing penalty costs, the model not only lowers total operational costs but also mitigates implicit costs such as reputational damage that are difficult to quantify directly. Establishing a cost framework that integrates transportation costs with expected penalty costs can fundamentally improve corporate cost structures and decision-making processes.

Relying solely on traditional transportation cost minimization does not lead to optimal solutions, as it overlooks implicit costs arising from delivery delays and reputation loss. Enterprises should therefore pay greater attention to various cost-influencing factors, shift away from cost-centric paradigms, and adopt more comprehensive and realistic optimization frameworks.

5.3 Research Limitations and Future Directions

This study has several limitations. Some assumptions are somewhat simplified, such as the independence of transportation times across different segments. Additionally, practical operational issues such as dynamic order arrivals and transshipment times are not explicitly considered. The analysis focuses exclusively on economic costs and does not incorporate policy-relevant factors such as carbon emissions.

Future research will extend this work by considering stochastic demand, real-time scheduling, and adaptive routing strategies. Moreover, carbon emission constraints and other sustainability objectives will be incorporated into multi-objective optimization models to better balance economic performance and environmental impact.

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Conflicts of Interest

The authors declare no conflict of interest.

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