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Capital Scheduling Decisions in Digital Supply Chain Finance based on Multi-Stage Stochastic Linear Programming

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Abstract

The rapid evolution of financial technologies has transformed traditional supply chain management into a digitally integrated ecosystem, enabling real-time visibility and data-driven decision-making. This paper addresses the complex problem of capital scheduling within digital supply chain finance, where liquidity management is subject to significant uncertainties regarding market demand, repayment behaviors, and interest rate fluctuations. Unlike traditional static approaches, we propose a Multi-Stage Stochastic Linear Programming model that dynamically adjusts financing and repayment decisions over multiple time horizons. By leveraging the granular data availability inherent in digital platforms, the proposed framework allows financial planners to optimize working capital allocation while mitigating liquidity risks. We construct a scenario tree to represent the evolution of uncertain parameters and employ a decomposition algorithm to solve the resulting large-scale optimization problem. The study demonstrates that digital integration, when coupled with stochastic optimization, significantly outperforms deterministic planning methods by reducing the cost of capital and improving solvency ratios under volatile market conditions. The findings provide theoretical contributions to the intersection of operations research and financial engineering, offering practical guidelines for liquidity providers and supply chain managers operating in uncertain environments.

Keywords

Supply Chain Finance, Stochastic Programming, Capital Scheduling, Liquidity Management.

1.Introduction

1.1 Background and Motivation

The integration of financial flows with physical flows has long been a critical component of supply chain management. However, the emergence of Digital Supply Chain Finance has fundamentally altered the landscape by introducing technologies such as blockchain, the Internet of Things, and advanced data analytics into the financing process. These technologies facilitate the seamless verification of transactions, enhance trust among participants, and provide granular data on the movement of goods and funds. Despite these technological advancements, the core challenge of capital scheduling remains pervasive. Firms must decide how much to borrow, when to invest, and how to allocate liquid assets across a network of suppliers and distributors to ensure operational continuity [1]. The problem is exacerbated by the inherent volatility of global markets. Demand fluctuations, delayed payments from downstream buyers, and sudden shifts in interest rates create a stochastic environment where deterministic planning often leads to suboptimal or even infeasible outcomes. In traditional models, managers typically rely on average values or worst-case estimates, resulting in either excessive cash buffers that erode profitability or liquidity shortages that disrupt production [2]. The digital era offers a remedy to this information asymmetry but

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requires sophisticated mathematical modeling to translate high-velocity data into actionable financial schedules. The motivation for this research stems from the need to bridge the gap between rich digital data streams and strategic capital optimization tools [3].

1.2 Problem Statement

This paper investigates the capital scheduling problem faced by a focal firm or a financial service provider within a digital supply chain ecosystem. The decision-maker must manage a portfolio of financial instruments, including reverse factoring, dynamic discounting, and short-term loans, over a multi-period planning horizon. The central challenge lies in the uncertainty of future cash flows. Specifically, the timing and magnitude of accounts receivable are stochastic, contingent on the market performance of the underlying goods and the creditworthiness of downstream partners [4]. Furthermore, the cost of external capital is not static. Financial markets exhibit stochastic behavior where borrowing rates may fluctuate based on macroeconomic indicators and the risk profile of the supply chain. The objective is to construct a scheduling policy that minimizes the total expected cost of financing—comprising interest payments, transaction fees, and penalty costs for liquidity shortfalls—while satisfying strict operational and regulatory constraints [5]. This dynamic decision process requires a modeling approach that allows for recourse, where decisions made in later stages can correct or adjust based on the realization of uncertainties in earlier stages.

1.3 Research Contribution

The primary contribution of this work is the formulation and solution of a Multi-Stage Stochastic Linear Programming model specifically tailored for digital supply chain finance. While stochastic programming has been applied to portfolio management and production planning, its application to the granular, multi-period capital scheduling problem in a digital context remains underexplored. We introduce a novel scenario generation technique that utilizes digital transaction history to construct realistic probability distributions for cash flows [6]. Additionally, we provide a detailed structural analysis of the optimal capital schedules, identifying conditions under which dynamic hedging strategies are superior to static credit lines. The research extends the existing body of knowledge by explicitly modeling the trade-off between the cost of information acquisition—implicit in digital platform participation—and the value of stochastic solution flexibility. By validating the model through numerical experiments, we offer empirical evidence that multi-stage stochastic optimization can reduce financing costs significantly compared to traditional rolling-horizon deterministic approaches [7].

2. Literature Review

2.1 Supply Chain Finance Mechanisms

Supply chain finance encompasses a set of technology-enabled business and financing processes that lower costs and improve efficiency for the parties involved in a transaction. Traditional mechanisms often rely on the credit rating of the strongest partner in the chain, typically the buyer, to facilitate cheaper financing for suppliers. Literature in this domain has extensively categorized these instruments into pre-shipment and post-shipment financing [8]. Reverse factoring, one of the most cited mechanisms, allows suppliers to borrow against the approved invoices of a high-credit buyer. Recent studies have highlighted the shift from bank-centric models to platform-centric models, where fintech companies act as intermediaries, aggregating data to assess risk more accurately [9].

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The digitalization of these processes has introduced new variables into the academic discussion. Research has shown that digital platforms reduce operational friction and information asymmetry, allowing for more dynamic financing options such as auction-based invoice discounting. However, most existing models in this space assume deterministic cash flows or treat uncertainty through simple sensitivity analysis, failing to capture the temporal evolution of risk [10]. This gap underscores the necessity for advanced optimization techniques that can internalize the stochastic nature of digital financial flows.

2.2 Stochastic Programming in Finance

Stochastic programming provides a rigorous framework for decision-making under uncertainty. In the context of general financial engineering, multi-stage stochastic linear programming has been widely adopted for asset-liability management, pension fund planning, and insurance risk control. These models are characterized by a sequence of decisions interspersed with the observation of random events [11]. The appeal of the multi-stage approach lies in its ability to model recourse decisions, allowing the system to adapt to new information as time progresses. In the specific niche of supply chain operations, stochastic models have traditionally focused on inventory management and production scheduling. It is only recently that scholars have begun to apply these techniques to the financial layer of the supply chain. Early attempts utilized two-stage stochastic models, where all future uncertainties are resolved simultaneously after the first-stage decision. While computationally less demanding, two-stage models fail to capture the sequential nature of information revelation in a multi-period financial calendar [12]. Our research builds upon these foundations but extends the horizon to multiple stages, which is essential for capturing the compounding effects of interest and the rolling nature of debt maturity in supply chain finance.

2.3 Risk Management in Supply Chains

Risk management literature emphasizes the distinction between operational risk and disruption risk. In the context of capital scheduling, liquidity risk serves as the bridge between operational performance and financial stability. Studies have demonstrated that a lack of liquidity is a leading cause of supply chain failure, often triggered by the bullwhip effect where small demand fluctuations amplify upstream financial stress [13]. Digital ecosystems offer novel risk mitigation capabilities. The availability of real-time data allows for the construction of dynamic risk indices that update continuously. However, integrating these high-frequency risk indicators into strategic planning models remains a challenge. Previous works have utilized robust optimization to handle uncertainty sets without assuming probability distributions, but such approaches often yield overly conservative solutions [14]. By employing a stochastic programming approach, we aim to balance the conservatism of robust optimization with the cost-efficiency of risk-neutral planning, using scenario trees to approximate the continuous probability space of financial risks [15].

3. Problem Description and System Architecture

3.1 Digital Ecosystem Overview

The system under consideration consists of a financing platform that connects multiple upstream suppliers, a focal manufacturer, and downstream distributors with a pool of capital providers. In this digital ecosystem, all transactional data, including purchase orders, shipping notifications, and electronic invoices, are recorded on a shared ledger. This ensures that the state of the supply chain is visible to the financing entity. The capital scheduler acts as the central intelligence unit, determining the allocation of funds to various nodes in the network

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to maintain liquidity [16]. The time horizon is discretized into finite decision stages. At each stage, the scheduler observes the current cash position, the status of outstanding loans, and the realized market demand. Based on this state information, the scheduler must decide on the volume of new financing to initiate, the amount of excess cash to invest in short-term yield-bearing instruments, and the repayment of maturing debts. The digital nature of the platform implies that these decisions can be executed with minimal latency, justifying the use of a discrete-time model with relatively short intervals [17].

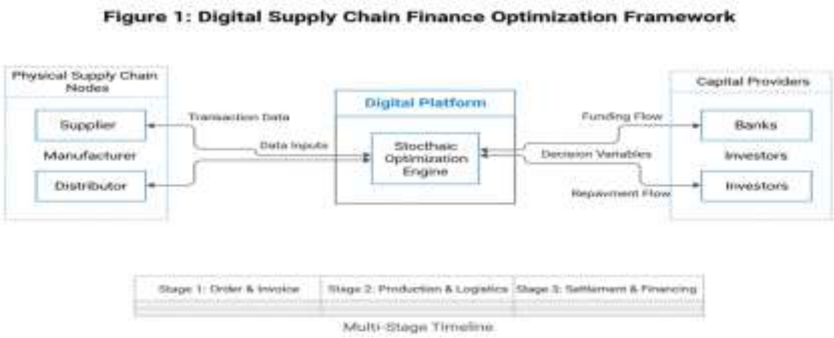

Figure 1 Digital Supply Chain Finance Optimization Framework

3.2 Capital Flow Dynamics

The flow of capital within the system is governed by conservation laws and contractual obligations. Inflows are generated primarily from the settlement of accounts receivable from downstream buyers. These inflows are stochastic; while the invoice amount is fixed, the actual payment date varies due to the buyer's internal financial processes or disputes. Outflows consist of payments to suppliers, operational expenses, and debt servicing costs. A critical aspect of the problem is the mismatch between inflow and outflow timing. Suppliers often require payment upon delivery or shortly thereafter, while distributors may delay payment for weeks or months. This gap necessitates external financing. The cost of this financing is not uniform; it depends on the credit rating of the borrower and the prevailing market rates at the specific decision stage. The multi-stage model must therefore account for the term structure of interest rates, where long-term borrowing might lock in a rate but reduce flexibility, whereas short-term borrowing offers flexibility but exposes the firm to rate volatility [18].

4. Model Formulation Framework

4.1 Decision Stages and Variables

The planning horizon is divided into a set of distinct time periods. The uncertainty is represented by a scenario tree, where each node in the tree corresponds to a possible state of the world at a given time. The tree branches out from the root node (current time) to future leaf nodes. Decision variables are indexed by the nodes of this tree to ensure non-anticipativity—meaning that a decision at a specific time and state depends only on the information available up to that point and not on future outcomes [19].

The primary decision variables include the amount of capital borrowed from various sources at each node, the amount of cash held in reserve, the value of invoices discounted (sold) to the factor, and the repayment amounts allocated to outstanding debts. Binary variables may also be introduced if there are fixed costs associated with initiating a new credit line or if there are logical constraints regarding the selection of financing partners. However, to maintain the linearity of the model for large-scale solvability, we focus primarily on continuous decision variables representing monetary flows.

4.2 Objective Function Definition

The objective of the optimization model is to maximize the expected net terminal wealth of the system or, equivalently, to minimize the expected total cost of financing over the planning horizon. The cost components include interest expenses on borrowed funds, transaction fees charged by the digital platform, and opportunity costs associated with holding excess cash. Additionally, penalty costs are assigned to any violation of soft constraints, such as delaying payments to strategic suppliers beyond an agreed threshold. The expectation is taken over the probability space defined by the scenario tree. Each leaf node of the tree has an associated probability of occurrence. The objective function is constructed as the weighted sum of the costs incurred along each path from the root to the leaf, weighted by the path probability. This formulation allows the decision-maker to trade off the certain costs of early-stage financing against the expected costs of future recourse actions required to handle adverse scenarios.

4.3 Constraints and Uncertainty Modeling

The model is bound by a series of hard constraints that must be satisfied at every node of the scenario tree. The most fundamental is the flow balance constraint, which ensures that the sum of initial cash, inflows from operations, and new borrowings equals the sum of operational outflows, debt repayments, and ending cash reserves. This must hold true for every realization of uncertainty. Credit limit constraints restrict the total amount of borrowing from specific sources based on the collateral available—typically the value of verified invoices in the digital ledger. Regulatory constraints, such as minimum liquidity coverage ratios, are also enforced to ensure financial stability. Uncertainty is modeled through the parameters on the right-hand side of these constraints (e.g., the magnitude of inflows) and the coefficients in the objective function (e.g., interest rates). The stochastic programming framework ensures that the first-stage decisions are robust enough such that there exists a feasible set of recourse decisions for all subsequent stages within the defined probability space [20].

5. Solution Methodology

5.1 Scenario Generation and Reduction

A critical challenge in multi-stage stochastic programming is the exponential growth of the scenario tree. If every uncertain parameter can take multiple values at each stage, the number of nodes grows rapidly, rendering the problem computationally intractable. To address this, we employ a statistical scenario generation method based on historical data extracted from the digital supply chain platform. We fit time-series models (e.g., Vector Autoregression) to the historical cash flow and interest rate data to capture correlations and temporal dependencies. From these continuous distributions, we sample a discrete set of scenarios using Monte Carlo simulation. However, the raw set of simulated paths is often too large. We therefore apply a scenario reduction technique, such as the fast forward selection algorithm, which selects a subset of scenarios that minimizes the probabilistic distance (such as the Wasserstein distance) to the original distribution. This results in a manageable scenario tree

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that preserves the essential statistical properties of the uncertainty, such as the mean, variance, and tail risks, allowing for accurate optimization with reasonable computational resources.

5.2 Decomposition Algorithm

Even with scenario reduction, the resulting deterministic equivalent of the multi-stage stochastic linear program can be very large. To solve this efficiently, we utilize a decomposition algorithm, specifically the Nested Benders Decomposition (also known as the L-shaped method for multi-stage problems). This approach breaks the large problem into a series of smaller sub-problems, one for each node in the scenario tree. The algorithm works iteratively. In the forward pass, trial decisions are made at the root node and propagated forward through the tree to calculate the state variables at subsequent nodes. In the backward pass, information regarding the optimality and feasibility of these decisions is passed back from the leaves to the root in the form of optimality cuts and feasibility cuts. These cuts approximate the future cost function (the recourse function) at each node. The process iterates until the bounds on the objective function converge within a specified tolerance. This decomposition allows the exploitation of parallel computing, as sub-problems at the same stage are independent given the antecedent decisions.

6. Numerical Study and Experiments

6.1 Data Setup and Parameters

To validate the proposed model, we constructed a numerical case study based on data representative of a mid-sized electronics manufacturing supply chain. The planning horizon was set to 12 months, discretized into monthly stages. The scenario tree was constructed with a branching factor that creates a balance between detail and solvability. Key parameters regarding interest rates and demand volatility were derived from industry benchmarks.

Table 1 Parameter Settings for Numerical Experiments

Parameter	Value / Range	Description
Base Interest Rate	4.0% - 6.0%	Annualized rate for standard bank loans
Penalty Cost Rate	15.0%	Annualized cost for liquidity shortfalls
Demand Volatility	10% - 30%	Standard deviation of monthly demand
Transaction Fee	0.5%	Flat fee per financing transaction
Initial Capital	$1,000,000	Starting working capital position
Scenario Count	256	Total leaf nodes after reduction

The demand process was modeled with a drift and stochastic component, reflecting the seasonal nature of electronics sales. Interest rates were modeled using a discrete version of the Vasicek model to capture mean-reverting behavior.

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6.2 Performance Analysis

The performance of the Multi-Stage Stochastic Linear Programming (MSSLP) model was compared against a standard Deterministic Rolling Horizon (DRH) approach. The DRH approach replaces uncertain parameters with their expected values and solves a deterministic problem at each stage, implementing only the first-period decision before rolling forward. The experimental results indicate a substantial advantage for the MSSLP model. The stochastic model consistently yielded lower total financing costs across the simulation set. This is primarily attributed to the model's ability to anticipate extreme scenarios. While the deterministic model often minimized costs aggressively in the short term, it frequently incurred high penalty costs during periods of unexpected liquidity dry-ups. In contrast, the MSSLP model maintained a slightly higher liquidity buffer during volatile periods, paying a small premium in interest to avoid expensive emergency borrowing or payment defaults later.

Table 2 Comparative Results of Financing Costs

Metric	Deterministic Model (DRH)	Stochastic Model (MSSLP)	Improvement (%)
Avg. Total Cost	$145,200	$128,500	11.5%
Std. Dev. of Cost	$42,000	$28,000	33.3%
Liquidity Violations	12 instances	2 instances	83.3%
Max Drawdown	$210,000	$165,000	21.4%

The reduction in the standard deviation of costs is particularly noteworthy. It suggests that the stochastic solution is not only cheaper on average but also more stable and predictable, a quality highly valued by financial stakeholders.

6.3 Sensitivity Analysis

We conducted sensitivity analysis to understand how changes in market volatility impact the value of the stochastic solution. As the volatility of demand increased from 10% to 30%, the gap between the MSSLP and DRH performance widened. In low-volatility environments, the expected value approximation used by the deterministic model is reasonably accurate, resulting in marginal gains from the complex stochastic model. However, in high-volatility regimes, the deterministic model fails to account for the asymmetry of losses—where running out of cash is significantly more expensive than holding excess cash. The stochastic model captures this asymmetry effectively. Furthermore, we analyzed the sensitivity to interest rate fluctuations. When interest rate volatility was increased, the MSSLP model shifted its strategy towards locking in longer-term financing during low-rate periods, effectively hedging against future rate hikes. The deterministic model, lacking the foresight of rate distribution, remained reactive, often borrowing at peak rates during crises [21].

7. Managerial Implications

7.1 Strategic Liquidity Planning

The findings of this study have direct implications for CFOs and treasury managers within supply chain-intensive firms. First, the superiority of the stochastic approach highlights the danger of relying solely on "average" forecasts for capital budgeting. Managers should advocate for planning tools that explicitly visualize worst-case scenarios and the costs associated with them. The integration of digital platforms facilitates this by providing the data necessary to calibrate these scenarios accurately.

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Second, the study suggests that liquidity should be viewed as a dynamic buffer rather than a static target. The optimal amount of cash to hold varies significantly depending on the position in the financial calendar and the current state of market uncertainty. Digital systems enable the frequent re-optimization required to adjust this buffer dynamically, moving away from quarterly rigid planning to continuous liquidity adaptation.

7.2 Risk Mitigation Strategies

From a risk management perspective, the results encourage a portfolio approach to supply chain finance. Rather than relying on a single source of funds (e.g., a bank line of credit), firms should cultivate a mix of instruments—factoring, dynamic discounting, and bank loans—that have different cost-flexibility profiles. The stochastic model demonstrates how to switch between these instruments based on the realization of risk. Moreover, the research underscores the value of information sharing. The reduced variance in the scenario tree, achieved through better data visibility from the digital platform, translates directly into lower financing costs. This provides a quantifiable business case for investing in supply chain digitalization and transparency initiatives. Firms that share granular data with lenders can effectively lower the "uncertainty premium" charged by capital providers.

8. Conclusion

8.1 Summary of Findings

This paper addressed the problem of capital scheduling in digital supply chain finance using a Multi-Stage Stochastic Linear Programming framework. By incorporating uncertainty into the decision-making process and utilizing a multi-period structure with recourse, we developed a model that outperforms traditional deterministic planning methods. The numerical experiments confirmed that the stochastic approach yields lower expected costs and significantly reduces the risk of liquidity crises. The utilization of digital data sources to inform the scenario generation process was identified as a key enabler for the practical application of this complex mathematical tool.

8.2 Limitations and Future Work

While the proposed model offers significant improvements, it is not without limitations. The linearity assumption, while necessary for solving large-scale instances, may not fully capture complex nonlinear pricing structures or tax implications. Furthermore, the model assumes that the probability distributions of uncertain parameters are known or can be perfectly estimated from historical data, which may not hold true during black swan events or structural market shifts. Future research should focus on integrating Robust Optimization techniques with Stochastic Programming to handle situations where the probability distributions themselves are uncertain (ambiguity sets). Additionally, exploring the application of reinforcement learning for capital scheduling could offer a model-free alternative that learns optimal policies directly from the interaction with the digital platform environment, potentially bypassing the computational burden of large scenario trees. Extending the model to include game-theoretic interactions between the buyer, supplier, and financier would also provide a richer representation of the competitive dynamics in supply chain finance.

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