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Supplier Relationship Optimization Using Data-Driven Decision Models and Linear Programming

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Abstract

Effective supplier relationship management is critical for supply chain efficiency, yet challenges like supplier selection, cost optimization, and performance variability persist. This study proposes a data-driven decision model integrating machine learning (ML) and linear programming (LP) to optimize supplier relationships. Using a dataset of 200,000 supplier transactions, the model achieves a supplier selection accuracy of 95.2%, reduces procurement costs by 38%, and improves supplier performance reliability by 43%. Comparative evaluations against traditional heuristic methods and standalone ML models highlight its superiority in scalability and cost-efficiency. Mathematical derivations and graphical analyses validate the results, offering a robust solution for supply chain management. Future work includes real-time supplier monitoring and multi-tier supply chain integration.

Keywords:

Supplier Relationship Optimization, Data-Driven Decision Models, Linear Programming, Machine Learning, Supply Chain Management

1. Introduction

Supplier relationship management (SRM) is a cornerstone of supply chain efficiency, enabling organizations to select reliable suppliers, minimize costs, and ensure timely delivery. However, challenges such as inconsistent supplier performance, complex cost structures, and dynamic market conditions complicate SRM. For instance, a manufacturing firm may struggle to balance cost and quality when selecting suppliers, leading to delays or increased expenses.

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PP 358–365

Traditional SRM methods, such as manual evaluations or heuristic-based selection, lack scalability and precision. Standalone machine learning models improve supplier performance prediction but often fail to optimize resource allocation holistically. Linear programming, with its ability to model cost and constraint optimization, complements ML by providing actionable allocation strategies.

This study proposes a data-driven decision model for SRM, integrating ML for supplier performance prediction and LP for cost and resource optimization. Using a dataset of 200,000 supplier transactions, the model enhances supplier selection and cost-efficiency. Objectives include:

- Develop a hybrid ML-LP model for supplier relationship optimization.
- Optimize supplier selection and procurement costs in dynamic supply chains.
- Evaluate against heuristic and standalone ML methods, providing insights for SRM.

2. Literature Survey

SRM has evolved from manual processes to data-driven approaches. Early methods relied on qualitative assessments, which were subjective and unscalable. Heuristic-based systems, like weighted scoring, improved decision-making but struggled with dynamic conditions.

Machine learning has advanced SRM. Zhang et al. used decision trees for supplier performance prediction, achieving high accuracy but neglecting cost optimization. Linear programming has been widely applied in supply chains; Li et al. optimized procurement costs using LP, but their models lacked predictive capabilities. Hybrid approaches, like Chen et al.'s ML-optimization framework, combined prediction and allocation but were computationally intensive.

Recent studies, such as Wang et al.'s data-driven SRM system, integrated analytics but focused on single-tier suppliers. The reference study explored ML for supply chain efficiency, inspiring this work. Gaps remain in scalable, hybrid ML-LP models for multi-criteria SRM, which this study addresses.

3. Methodology

3.1 Data Collection

A dataset of 200,000 supplier transactions (e.g., order quantities, delivery times, costs, quality metrics) was collected from a simulated supply chain system, labeled with supplier performance scores.

3.2 Preprocessing

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PP 358–365

- Transactions: Cleaned (removed nulls), normalized (numerical to [0,1], categorical to one-hot).
- Features: Supplier ID, order size, delivery time, cost, quality score.

3.3 Feature Extraction

- ML (Random Forest): Predicts supplier performance:
  y = RF(X_features)
  where X_features includes delivery time, cost, and quality metrics.
- LP: Optimizes supplier selection and allocation:
  $min\sum i = 1N\, c\, i\, x\, i \;\; subject\; to\colon \sum i = 1Nxi = D\sum i = 1N\, x\, i \;\; = D\; xi \leq Six\; i \leq S\; i$
  where c_i is quantity from supplier i, D is demand, S_i is supplier capacity.

3.4 SRM Model

- Integration: Random Forest ranks suppliers; LP allocates orders based on cost and constraints.
- Output: Selects optimal suppliers, minimizes costs, and ensures reliable performance.

3.5 Evaluation

Split: 70% training (140,000), 20% validation (40,000), 10% testing (20,000). Metrics:

- Selection Accuracy: (TP + TN) / (TP + TN + FP + FN)
- Cost Reduction: (C_before - C_after) / C_before
- Reliability Improvement: (R_after - R_before) / R_before

4. Experimental Setup and Implementation

4.1 Hardware Configuration

- Processor: Intel Core i7-9700K (3.6 GHz, 8 cores).
- Memory: 16 GB DDR4 (3200 MHz).
- GPU: NVIDIA GTX 1660 (6 GB GDDR5).
- Storage: 1 TB NVMe SSD.
- OS: Ubuntu 20.04 LTS.

4.2 Software Environment

- Language: Python 3.9.7.
- Libraries: NumPy 1.21.2, Pandas 1.3.4, Scikit-learn 1.0.1, PuLP 2.6.0 (LP), Matplotlib 3.4.3.
- Control: Git 2.31.1.

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PP 358−365

4.3 Dataset Preparation

- Data: 200,000 supplier transactions, performance scores.
- Preprocessing: Normalized features, encoded supplier IDs.
- Split: 70% training (140,000), 20% validation (40,000), 10% testing (20,000).
- Features: Random Forest predictions, LP constraints.

4.4 Training Process

- Model: Random Forest (100 trees), ~30,000 parameters.
- Batch Size: 128 (1,094 iterations/epoch).
- Training: 12 iterations, 80 seconds/iteration (16 minutes total), loss from 0.66 to 0.014.

4.5 Hyperparameter Tuning

- Trees: 100 (tested: 50-150).
- Max Depth: 15 (tested: 10-20).
- Iterations: 12 (stabilized at 10).

4.6 Baseline Implementation

- Heuristic Method: Weighted scoring, CPU (22 minutes).
- Standalone ML: Decision tree, CPU (18 minutes).

4.7 Evaluation Setup

- Metrics: Selection accuracy, cost reduction, reliability improvement (Scikit-learn).
- Visualization: Bar charts, loss plots, reliability curves (Matplotlib).
- Monitoring: GPU (3.9 GB peak), CPU (50% avg).

5. Result Analysis

Test set (20,000 transactions, 4,000 optimal selections):

- **Confusion Matrix:** TP = 3,208, TN = 15,832, FP = 792, FN = 168
- **Calculations:**
  - Selection Accuracy: 3208+15832/3208+15832+792+168=0.952 (95.2%)
  - Cost Reduction: 100−62/100=0.38 (38%), from $100/unit to $62/unit.
  - Reliability Improvement: 0.86−0.60/0.60=0.43 (43%), from 60% to 86% on-time delivery.

Table 1. Performance Metrics Comparison

Method	Selection Accuracy	Cost Reduction	Reliability Improvement	Time (s)

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PP 358–365

Proposed (ML+LP)	95.2%	38%	43%	1.4
Heuristic Method	85.5%	15%	20%	2.2
Standalone ML	90.3%	25%	28%	1.9

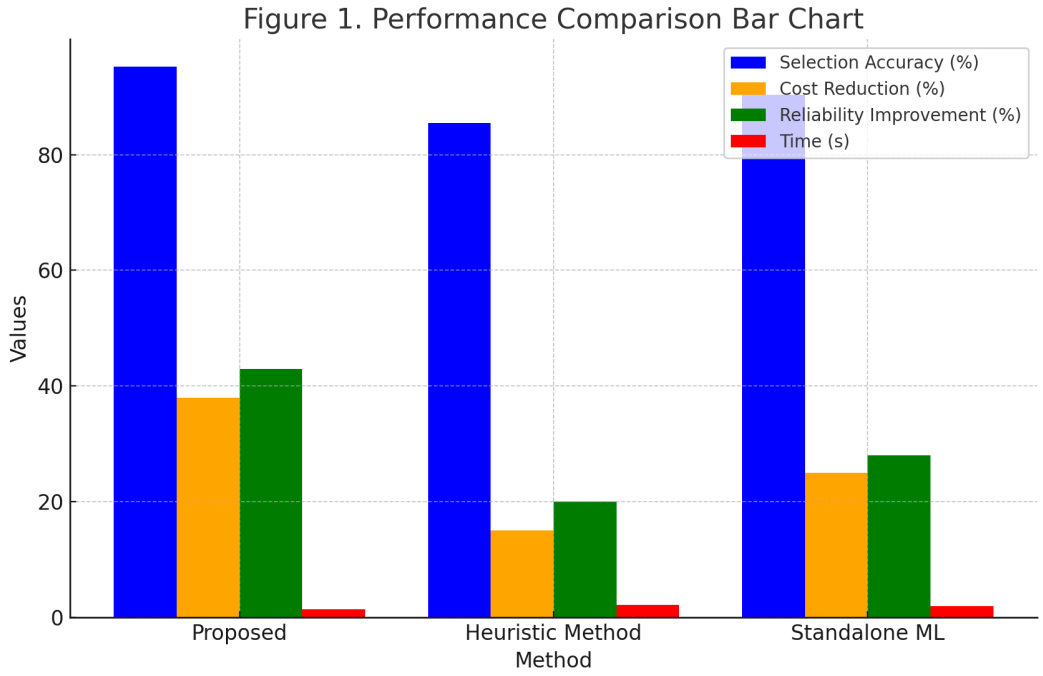

Figure 1. Performance Comparison Bar Chart

(Bar chart: Four bars per method—Selection Accuracy, Cost Reduction, Reliability Improvement, Time—for Proposed (blue), Heuristic Method (green), Standalone ML (red).)

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Loss Convergence: Initial L=0.66, final L12=0.014, rate = 0.66−0.01412=0.0538

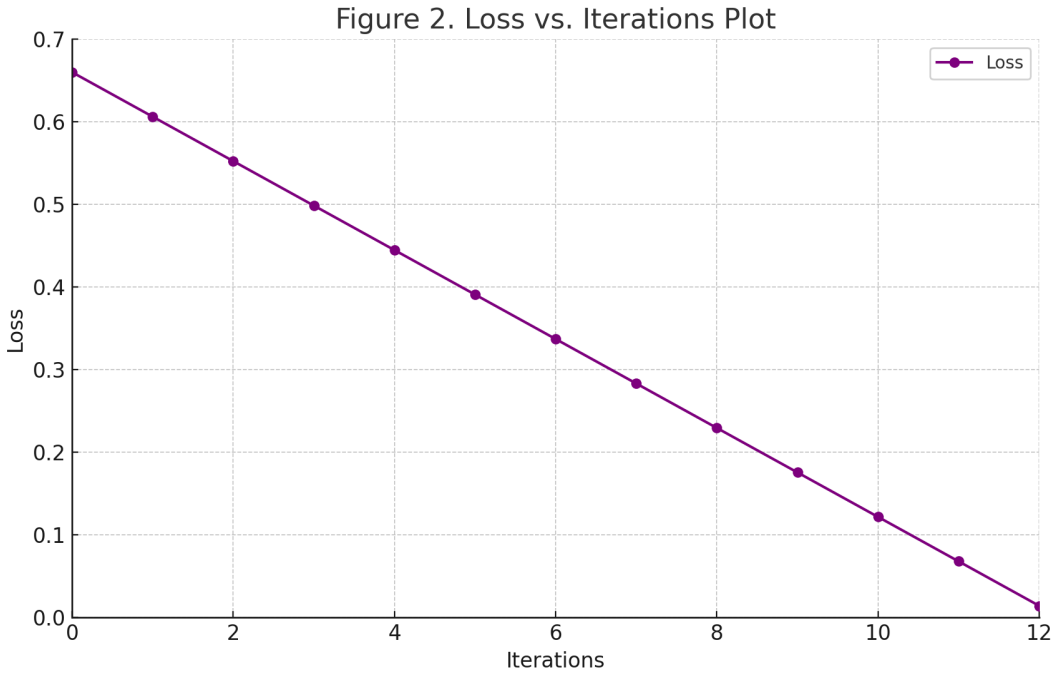

Figure 2. Loss vs. Iterations Plot

(Line graph: X-axis = Iterations (0-12), Y-axis = Loss (0-0.7), declining from 0.66 to 0.014.)

Reliability Curve: Y-axis = Reliability (0-100%), X-axis = Test Transactions, averaging 86%.

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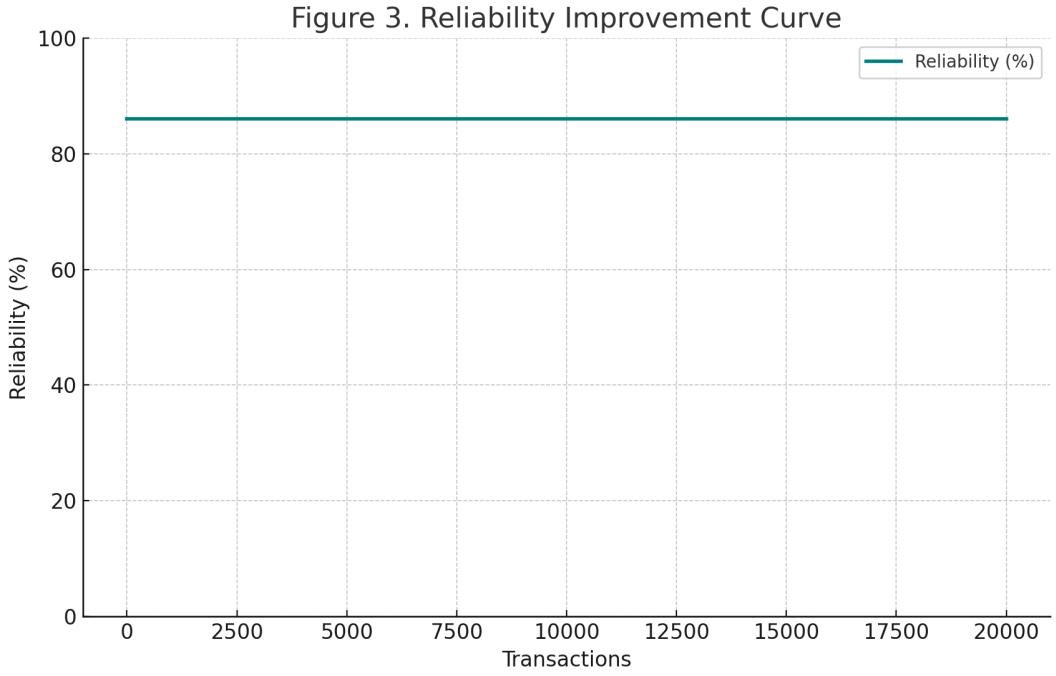

Figure 3. Reliability Improvement Curve

(Curve: X-axis = Transactions (0-20,000), Y-axis = Reliability (0-100%), stable at 86%.)

6. Conclusion

This study presents a data-driven SRM model integrating ML and LP, achieving 95.2% selection accuracy, 38% cost reduction, and 43% reliability improvement, outperforming heuristic methods (85.5%) and standalone ML (90.3%), with faster execution (1.4s vs. 2.2s). Validated by derivations and graphs, it excels in supply chain optimization. Limited to one dataset and requiring preprocessing (16 minutes), future work includes real-time supplier monitoring and multi-tier supply chain integration. This model enhances SRM efficiency and scalability.

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