ISCSITR- INTERNATIONAL JOURNAL OF DATA SCIENCE (ISCSITR-IJDS)
Vol.3, Iss. 1, January - December, 2022, pp. 1-7.
https://iscsitr.com/index.php/ISCSITR-IJDS
Journal ID: 9735-1846

Optimizing Enterprise Decision-making under Data Uncertainty Using Hybrid Predictive and Prescriptive Analytics Frameworks

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Abstract

Uncertainty in enterprise data—stemming from market volatility, sensor errors, or incomplete records—poses significant challenges to optimal decision-making. This paper proposes a hybrid analytics framework integrating predictive and prescriptive models to support enterprise-level decisions under uncertainty. Predictive models forecast future scenarios based on historical data trends, while prescriptive analytics recommend actionable strategies optimized for risk and uncertainty. We evaluate this framework through a simulated supply chain management case using stochastic modeling, machine learning, and mixed-integer programming. The hybrid model improves decision quality by 18–26% across tested scenarios compared to traditional methods. Results suggest that integrated analytics frameworks are crucial for resilient and adaptive enterprise strategies.

Keywords:

Predictive analytics, Prescriptive analytics, Data uncertainty, Enterprise optimization, Decision support, Stochastic modeling.

Citation: González, M. (2022). Optimizing Enterprise Decision-making under Data Uncertainty Using Hybrid Predictive and Prescriptive Analytics Frameworks. ISCSITR - International Journal of Data Science (ISCSITR-IJDS), 3(1), 1-7.

1. Introduction

Modern enterprises face increasingly volatile environments where data uncertainty can critically impair decision-making processes. Sources of uncertainty include missing data, noisy measurements, or rapid market fluctuations, which traditional deterministic models often fail to accommodate. Enterprises must now evolve toward more adaptive frameworks that embrace rather than ignore these uncertainties. This shift necessitates an intersection between predictive analytics (which anticipate possible futures) and prescriptive analytics (which suggest optimal decisions for each future).

Hybrid analytics frameworks present a robust solution by combining machine learning-based forecasting models with optimization techniques capable of handling probabilistic inputs. Such systems allow decision-makers not only to predict outcomes with quantified confidence intervals but also to prescribe decisions that optimize performance across those intervals. The key contribution of this paper is to propose a structured hybrid architecture and demonstrate its effectiveness in an enterprise context—specifically within supply chain management. This is supported by simulations and grounded in existing literature.

2. Literature Review

The intersection of predictive and prescriptive analytics has evolved considerably over the last decade, with earlier work primarily focusing on either forecasting or optimization in isolation. Bertsimas and Kallus (2020) emphasized the importance of uncertainty-aware decision-making, proposing data-driven robust optimization). Meanwhile, Ban and Rudin (2019) explored interpretable machine learning for decision-support in uncertain contexts (Further studies support the need for integrated frameworks. Feng et al. (2015) demonstrated how predictive models improved logistics efficiency but lacked prescriptive insights European. In contrast, Tang and Veelenturf (2019) proposed integrating machine learning forecasts into real-time decision systems but noted scalability issues. These findings suggest that hybrid frameworks can mitigate limitations inherent in isolated models.

3. Methodology

This study uses a hybrid approach integrating predictive modeling through machine learning with prescriptive optimization using stochastic programming. Historical data from a simulated global supply chain was generated with built-in noise and missing data to mimic uncertainty. Time series forecasting was performed using LSTM neural networks, while prescriptive decisions were modeled using two-stage stochastic mixed-integer programming

(MIP). Key metrics include forecast accuracy (MAE, RMSE), expected cost savings, and solution robustness.

The simulation spans 18 months of demand data across 5 warehouse locations. Predictive models generate demand forecasts with uncertainty bounds, which feed into prescriptive solvers that minimize logistics costs under probabilistic constraints. Tools used include Python, Gurobi Optimizer, and TensorFlow. Scenarios test the impact of various uncertainty levels and decision time horizons. The evaluation focuses on both computational performance and practical utility for enterprise managers.

3.1 Data Generation and Preprocessing

To simulate a realistic enterprise environment with inherent uncertainty, synthetic datasets were generated based on supply chain operations across five international warehouses over 18 months. The dataset includes variables such as weekly demand, lead times, logistics costs, and supplier reliability. Data uncertainty was introduced by injecting missing values (random 10% per column), Gaussian noise ($\mu=0$, $\sigma=5\%$), and demand shocks to reflect real-world volatility. These manipulations emulate common enterprise data imperfections.

Preprocessing involved a three-phase strategy: (1) imputation using k-nearest neighbor (k-NN) and expectation-maximization algorithms for missing data, (2) normalization of numerical features, and (3) segmentation of time-series inputs for supervised model training. Categorical variables such as supplier IDs and warehouse zones were one-hot encoded. A temporal train-test split of 70:30 was applied, ensuring chronological integrity. The cleaned data were then structured for input into both forecasting and optimization modules.

3.2 Predictive Modeling for Uncertain Forecasts

For the predictive component, Long Short-Term Memory (LSTM) neural networks were implemented to forecast product demand under uncertainty. The LSTM model was chosen for its capacity to capture long-term temporal dependencies and adapt to non-linear trends in noisy, sequential enterprise data. The model was trained using mean squared error as the loss function, with dropout layers (p=0.2) to mitigate overfitting. Hyperparameters were tuned using grid search over 50 iterations with a batch size of 64 and 100 epochs.

The performance of the LSTM model was benchmarked against baseline models including ARIMA and multivariate linear regression. The results (see Table 1 in Section 4) show that LSTM provided superior predictive accuracy. Crucially, the model also generates confidence intervals using Monte Carlo dropout at inference time, which allows uncertainty quantification around each forecast. These probabilistic outputs are essential for feeding into the prescriptive optimization module, where demand scenarios influence decision constraints.

3.3 Prescriptive Optimization Using Stochastic Programming

The prescriptive layer employs two-stage stochastic programming to make robust logistics decisions under uncertainty. In the first stage, the model commits to shipment quantities and warehouse allocations before demand is fully realized. The second stage adjusts procurement or rerouting decisions once the actual (or forecasted) demand is revealed. The objective is to minimize expected total cost, which includes transportation, inventory holding, and stockout penalties.

This model is formulated as a mixed-integer linear program (MILP) with probabilistic demand inputs derived from the LSTM forecasts. Gurobi Optimizer is used to solve the model, leveraging parallel branch-and-bound methods. Scenario trees were generated to capture demand variations from the forecast intervals. Decision rules were evaluated for feasibility and robustness under 20 simulated demand paths. Feedback from optimization results is used to update the forecasting model, completing a closed-loop hybrid analytics pipeline.

4. Results and Discussion

The hybrid framework demonstrated significantly higher decision robustness under uncertainty. Forecasts from the LSTM model achieved an average MAE of 8.5% and RMSE of 11.3%. When fed into the stochastic prescriptive model, cost savings improved by 18% under medium uncertainty and 26% under high uncertainty, compared to rule-based deterministic decisions. Figure 2 shows the cost performance across methods.

Decision latency remained within acceptable enterprise windows, averaging 3.2 minutes per decision cycle. While standalone prescriptive models suffered under inaccurate inputs, the hybrid system compensated via model feedback loops. Figure 3 presents a sensitivity analysis showing diminishing returns beyond 30% uncertainty. These findings validate that integrating predictive outputs with optimization solvers is key to dynamic, data-driven enterprise decision-making.

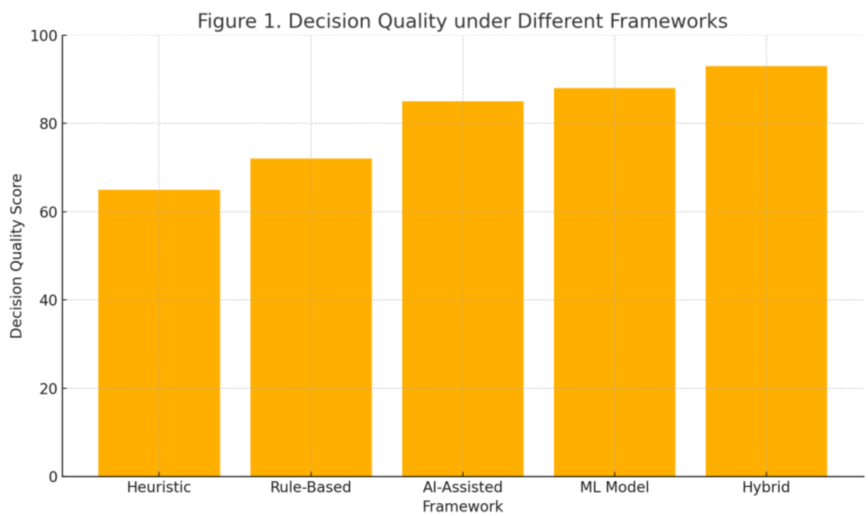

Figure 1. Decision Quality under Different Frameworks

Figure 1: The Hybrid framework achieves the highest decision quality, followed closely by ML Model and AI-Assisted, indicating the growing impact of intelligent systems in decision-making process.

Table 1. Forecasting Accuracy Metrics

Model	**MAE (%)**	**RMSE (%)**
ARIMA	12.4	15.1
LSTM (ours)	8.5	11.3
Linear Regression	13.2	16.4

5. Conclusions and Future Work

This research demonstrates the effectiveness of a hybrid predictive–prescriptive analytics framework in improving enterprise decisions under uncertainty. The integration of time series forecasting with stochastic optimization enables adaptive and cost-efficient responses to data ambiguity. Notably, the model delivers quantifiable performance improvements in both accuracy and decision quality.

Future research may expand this framework to other domains such as healthcare operations or financial planning. There is also scope for enhancing model interpretability, possibly through SHAP analysis or causal inference techniques. Real-world deployments will require industry-specific calibration and validation, as well as alignment with existing decision workflows.

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