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Research on Cross-Border Tax Compliance Management and Risk Prevention and Control of Enterprises under the Background of Global Tax Transparency

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Abstract: Procurement, production, inventory, and sales flow processing interact with each other, but traditional cost management focuses more on post-event accounting and struggles to directly support rolling decision-making. Based on two sets of normal operation transaction records from ERPsim, this study constructs a standardized process cost chain within the ERP process boundary. The study uses a rolling-up quantile LightGBM to generate P10, P50, and P90 demand scenarios and compares the high-buffer moving average rule, the service-constrained expected cost strategy, and the risk screening strategy among 847 shared strategies. Two cross-operation online replays show that the quantile LightGBM's P50 prediction WMAPE is 43.85% and 38.74%, respectively, slightly lower than the moving average. The risk screening strategy does not consistently outperform the high-buffer rule calibrated during development: in MAS1→MAS2, it is inferior in cost, immediate fulfillment rate, and actual record box CVaR90; in MAS2→MAS1, its cost is only 0.30% lower, the difference is not significant, and the tail cost is higher. The results indicate that a slight decrease in prediction error does not automatically translate into operational benefits. When using complex controls, enterprises also need to make judgments based on service buffers, procurement lead times, and tail risks .

1 Introduction

Order fluctuations, changes in raw material supply, and delivery pressures all affect the daily operations of enterprises. The costs incurred by the procurement, production, warehousing, and sales departments are not simply added together, but are the result of continuous decision-making in multiple stages. Slow raw material replenishment will limit production, insufficient production will compress the finished product buffer, and insufficient inventory may lead to a backlog in subsequent sales. Artificial intelligence and prescription analysis can transform scattered data into resource allocation suggestions, and therefore have been used in supply chain resilience and operational decision-making research [1]. However, whether more complex prediction and optimization algorithms can stably reduce costs still needs to be fairly compared with reasonable operating rules.

Traditional cost management mainly explains where costs have already occurred, making it difficult to directly support decisions on procurement volume, production volume, and inventory buffer at the next point in time. Existing research has combined simulation, data modeling, and planning optimization for master plan updates under disturbance conditions [2]; some studies have also discussed the role of artificial intelligence in replenishment decisions around inventory distortion [3]. However, many studies still treat demand forecasting, inventory management, and production planning separately, and pay insufficient attention to the linkage between procurement, production, inventory, and sales flow processing within the same ERP process. It is also important to note that some complex algorithms are only compared with uncalibrated empirical rules. In this case, the advantage presented by the algorithm may come from a higher safety buffer, rather than from the forecasting or optimization itself.

This study does not presuppose that intelligent strategies are necessarily superior to fixed rules; instead, it examines the counterfactual cost control results of different strategies within the boundaries of the ERP process. The study uses publicly available ERP transaction records to construct a standardized process cost chain for procurement-production-inventory-sales flow processing, and incorporates quantile forecasting, demand scenarios, and multi-objective selection into the same rolling decision-making process. Based on this, the study uses a high-buffered moving average rule calibrated during the development phase as a strong baseline to test whether complex strategies can develop a stable advantage across operational replays and pre-set stress scenarios. The study does not interpret simulation results as actual enterprise book costs, nor does it directly equate sales invoice quantities with original customer orders or observed performance indicators.

2. Research Boundaries and Theoretical Foundations

2.1 Definition of full-chain costs within the boundaries of ERP processes

The term "full-chain operating cost" used in this study refers only to process costs that are traceable within the ERP process and directly affected by current procurement, production, and inventory decisions. Cost items include raw material procurement costs, production conversion costs, raw material and finished goods inventory holding costs, sales flow processing costs, and backlog costs resulting from unmet sales flows. The raw data includes transaction records such as raw material receipts, raw material requisitions, finished goods warehousing, and sales invoicing, but does not provide directly correlated customer order headers, promised delivery dates, carrier quotations, actual inventory records, or company financial statements. Therefore, this study uses the SD00 invoicing quantity as a proxy variable for realized sales flows and calculates "immediate fulfillment rate" and backlog in a counterfactual recursive approach. This study does not present these two indicators as actual delivery KPIs already observed in the original ERP system.

This research boundary allows procurement, production, inventory, and sales flow processing to be integrated into a single state system. The study can thus observe how front-end decisions are transmitted to subsequent backlogs and costs. However, transportation settlements, actual payment cycles, customer default compensation, and financial book costs are not directly observed, and these are not included in the conclusions of this study . The role of standardized process costs is to compare the consequences of different strategies under the same transaction structure, initial state, and cost parameters, rather than to estimate a company's true profit or cash flow.

2.2 Improved prediction does not necessarily lead to improved control.

Probabilistic forecasting can transmit the uncertainty of demand to inventory decisions in the form of intervals or quantiles, and is therefore more suitable for handling fluctuating demand than single-point forecasting [4]. However, there is no fixed one-to-one correspondence between forecast accuracy and inventory performance. Existing studies have found that forecasting methods, service targets, review cycles, lead times and cost structures all affect the impact of forecasting errors on inventory costs [5]. When high-buffered fixed rules have covered most of the fluctuations, a small increase in forecast accuracy may not bring significant process cost advantages.

When machine learning is used for inventory control, common approaches include “post-prediction optimization” and “joint prediction and decision-making”. Practical applications are still affected by data structure, constraint completeness and baseline selection [6]. Based on this understanding, this study compares high-buffered fixed rules, service-constrained expected cost strategies and risk screening strategies in the same state recursion, capacity proxy and parameter boundary. The study does not attempt to prove that a certain method is better under all conditions, but focuses on the actual position of each strategy among cost, service and tail risk.

3. Data Sources and Research Design

3.1 Data Sources, Sample Construction, and Process Mapping

This study uses two publicly available sets of normal operation transaction records, MAS1 and MAS2, from ERPsim. ERPsim records the purchasing, production, inventory, sales, and financial transactions of a virtual manufacturing enterprise according to SAP standard business processes. Therefore, the data represents ERP operation simulation records in a serious game environment and is not equivalent to real enterprise accounting. MAS1 contains 92,985 records and 154 5-minute record bins, while MAS2 contains 59,378 records and 110 5-minute record bins. The study retains three finished products: AA-F12, AA-F15, and AA-F16, along with their corresponding six raw materials and two packaging materials. The study corrects the original timestamps according to the start time of the operation and aggregates data in 5-minute increments. This processing only changes the granularity of the analysis and does not alter the quantity and total value of each material in each record bin.

Table 1 ERP Transaction Records, State Variables, and Research Boundaries

Business processes	Key transaction records	Data usage in the model	Conclusion Boundaries
Raw material procurement	Materialzugang-RMWE; Supplier Invoice	Estimate raw material unit price, form purchase quantity, and status of purchases in transit.	Not simulating actual payment cycles and cash flow
Production conversion	Materialabgang-RMRU; Materialzugang-RMRU	Estimate material input relationships, production volume and conversion costs	Actual equipment efficiency is not evaluated.
Warehouse occupancy	Recursive balance of raw materials, finished products and in-transit purchases	Incurring raw material and finished goods inventory holding costs	Not equivalent to actual inventory records or warehouse rental fees
Sales traffic processing	Sachkontenbuchung-SD00	As a sales traffic agent, calculate counterfactual instant gratification and backlog.	Not equivalent to the original order arrival or actual delivery KPI

Table 1 shows the correspondence between transaction records and model variables. The study reconstructs material input and production conversion using raw material receipt, raw material requisition, and finished product warehousing, and calibrates the sales flow proxy using sales invoice quantities. To avoid cross-operation information leakage, MAS1→MAS2 and MAS2→MAS1 each constitute two cross-operation online replays. Each replay uses the first 24 record boxes to form a common initial state and demand lag, with the remaining record boxes used for box-by-box decision-making and evaluation. After the model goes live, every four record boxes are retrained using only the already released sales flow. Therefore, this study defines this process as "online replay after a cross-operation cold start," rather than a completely frozen offline external test.

3.2 Cost Scope and Status Derivation

The study calculates the unit value of raw materials based on the transaction amount and quantity. Utilizing raw material requisition and finished product warehousing data from the development and operation phase, the study estimates material input coefficients using non-negative least squares method; the coefficients of determination for the eight raw materials or packaging materials range from 0.526 to 0.739. Finished product conversion costs are obtained by deducting the material value from the finished product warehousing value, and a minimum positive value is set to avoid zero-cost production. Since the data does not disclose warehouse rental fees, actual freight costs, and default compensation, the study sets uniform standardized coefficients for inventory holding, sales flow processing, backlog, and procurement processing, taking 0.25% of inventory value, 1.5% of sales value, 25% of backlog sales value, and 0.4% of procurement value, respectively.

the first $t$record box can be written as:

$$C_t = C_t^{pur} + C_t^{pro} + C_t^{inv} + C_t^{ful} + C_t^{back}$$

Here, C_t^{pur}, C_t^{pro}, C_t^{inv}, $C_t^{ful}$and C_t^{back}represent purchasing, production conversion, inventory holding, sales flow processing, and backlog costs, respectively. Purchasing is priced at the time of order placement to avoid treating in-transit purchases as cost-free resources; at the end of the replay, the ending backlog is cleared at the sales value of one product, and the remaining raw materials, finished goods, and in-transit purchases are added at the holding cost of one log box. This treatment reduces the tendency of finite-term models to push costs beyond the end of the period, but it cannot completely eliminate boundary sensitivity.

4. Quantile Prediction and Multi-Objective Rolling Control Model

4.1 Rolling Quantiles LightGBM Prediction

This study uses quantile LightGBM (quantile gradient boosting, QGB) to generate P10, P50, and P90 demand forecasts. The model targets the logarithmically transformed sales flow and minimizes the 0.1, 0.5, and 0.9 quantile losses, respectively.

$$\min_f \sum_{i=1}^{n} \rho_\tau \left[\ln(1 + y_i) - f_\tau(x_i)\right], \quad \tau \in \{0.1, 0.5, 0.9\}$$

The model inputs include lag values for bins 1, 2, 3, 4, 6, 12, 18, and 24, as well as rolling mean, standard deviation, non-zero frequency, short-term trend, product identifier, and forecast step size for bins 3 through 24. The model directly forecasts the next four bins and uses segmented conformal corrections using residual blocks from the development run. When a one-step residual released during the test run significantly widens, the model only allows widening the scenario width, not narrowing it. This design does not hide forecast errors within a fixed safety stock but instead directly passes the forecast range to subsequent purchasing and production decisions.

4.2 Production, Procurement, and Status Updates

For each product, the model determines the target production gap based on median forecasts, high quantile coverage, existing backlogs, and finished goods inventory:

$$z_{p,t} = \hat{y}_{p,t}^{0.50} + \alpha\left(\hat{y}_{p,t}^{0.90} - \hat{y}_{p,t}^{0.50}\right) + \gamma B_{p,t-1} - I_{p,t-1}$$

$$q_{p,t} = \min\{\bar{q}_p, \max\left(0, z_{p,t}\right)\}$$

Here, $\bar{q}_p$represents the estimated production ceiling during development and operation, $B_{p,t-1}$is the initial backlog, $I_{p,t-1}$and is the initial finished goods inventory, αused to control the coverage of P90 demand and $\gamma$to adjust the response intensity of existing backlogs. Production first consumes currently available raw materials, then forms finished goods inventory; thereafter, raw material procurement is calculated based on the state after production and before the realization of current sales flow. The target raw material gap and actual procurement quantity are as follows:

$$v_{r,t} = \sum_p b_{rp}\, \tilde{q}_{p,t+L} + \beta \sum_p b_{rp}\, \sigma_p - R_{r,t}^{post} - P_{r,t}^{pipe}$$

$$u_{r,t} = \max\left(0, v_{r,t}\right)$$

Wherein, $b_{rp}$is $r$the material consumption coefficient of $\tilde{q}_{p,t+L}$the product corresponding to the raw material, is $p$the target production volume required after $\beta$the lead time , $L$is the raw material buffer coefficient, $\sigma_p$is the sales flow fluctuation during development and operation, is $R_{r,t}^{post}$the raw material inventory after production, $P_{r,t}^{pipe}$ and is the procurement volume in transit. The procurement lead time baseline is set at 1 record box, and is expanded to 2 record boxes in the robustness test.

4.3 ε-Constraint Search and Fair Comparison

Since the policy only has αthree continuous variables, and β, γthis study uses a deterministic grid instead of a low-population evolutionary algorithm. $\alpha$and βtake 11 values from 0 to 2.5 $\gamma$and 7 values from 0 to 1.5, respectively, resulting in 847 shared candidate policies. At each decision point, 20 equally probable demand scenarios, spanning four record boxes, are generated from the development and operation residual blocks. The service constraint policy is solved first:

$$\min_\theta E[C(\theta)] \quad \text{s.t.} \quad E[FR(\theta)] \geq \varepsilon$$

Here, FRrepresents the immediate satisfaction rate of the scenario, with service thresholds of 95%, 93%, and 90%, relaxed only when there is no 95% feasible solution in the current state. B2 selects the strategy with the lowest expected cost under this constraint. Proposed, under the same service constraint, selects only the strategy with the lowest scenario CVaR90 from those strategies whose expected cost does not exceed 102% of the lowest feasible cost. Under 20 equally probable scenarios, the scenario CVaR90 is the average cost of the two scenarios with the highest total planning time:

$$\mathrm{CVaR}_{0.90}[C] = \frac{1}{2} \sum_{s \in \mathrm{Top2}} C_s$$

The screening rule draws on the basic idea of the ε-constraint method to handle cost and service conflicts[7] and uses CVaR to supplement extreme losses that are difficult to reflect by average cost[8]. B1c is a high-buffered moving average rule calibrated only during development runs, with its parameters fixed before external playback begins. B2 and Proposed share state updates, capacity proxies, and parameter boundaries with B1c. The actual record box CVaR90 is calculated based on the single-box process cost driven by the actual sales flow in playback and is strictly distinguished from the scenario CVaR90 used when selecting the strategy [9].

5. Experimental Results and Analysis

5.1 Cross-operation prediction results

Table 2 presents the prediction results for the two playback directions. In MAS1→MAS2, the P50 WMAPE of QGB is 43.85%, slightly lower than MA6's 44.01%; in MAS2→MAS1, the P50 WMAPE of QGB is 38.74%, lower than MA6's 41.65%. The coverage rates of the two P10-P90 intervals are 87.55% and 85.56%, respectively, both higher than the nominal 80% coverage level. The results indicate that the quantile model can provide a relatively wide range of demand uncertainty, but the median prediction error is still relatively high, and it cannot be described as a high-precision prediction [10-13].

Table 2 Demand Forecast Results for Online Playback Across Operations

Playback direction	Model	MAE	RMSE	WMAPE/%	P10—P90 coverage rate /%
MAS1→MAS2	QGB-P50	3560.68	4891.05	43.85	87.55
MAS1→MAS2	MA6	3573.68	4877.35	44.01	—
MAS2→MAS1	QGB-P50	3494.21	4593.42	38.74	85.56
MAS2→MAS1	MA6	3757.02	4870.58	41.65	—

Forecast results are not directly transmitted to control results in a linear fashion. Probabilistic forecasting studies show that inventory performance is affected not only by point forecast errors but also by safety buffers and inventory rules. Based on this, subsequent comparisons do not deduce that "dynamic strategies are necessarily better" based on "lower QGB errors," but rather directly examine the costs, immediate satisfaction rates, and actual tail costs of different control rules in actual sales flow replay [14-17].

5.2 Control results of the main rewind.

Table 3 shows that in the MAS1→MAS2 process, the total standardization cost of B1c is 518.07 × 10^4, the immediate satisfaction rate is 97.79%, and the actual recording box CVaR90 is 11.22 × 10^4. The costs of B2 and Proposed are 1.51% and 1.17% higher than B1c, respectively, with immediate satisfaction rates lower by 5.16 and 4.50 percentage points, respectively, and actual recording box CVaR90 higher by 10.72% and 10.17%, respectively. In this playback direction, the high-buffered moving average rule simultaneously exhibits lower average cost, higher immediate satisfaction rate, and lower tail cost [18-20].

The results in MAS2→MAS1 are closer. The cost of Proposed is 875.61×10^4, only 0.30% lower than B1c, but the immediate satisfaction rate is 0.11 percentage points lower, and the actual bin CVaR90 is 8.28% higher. B2 also only achieves a cost reduction of about 0.30%, accompanied by a lower immediate satisfaction rate and higher tail costs. The study used 7 bins as blocks for 5,000 block-moving bootstraps. The results show that the average single-bin cost difference between Proposed and B1c is 555.74 in MAS1→MAS2, with a 95% confidence interval of [−1661.07, 2786.92] and a two-sided empirical probability of 0.6216; in MAS2→MAS1 it is −206.98, with an interval of [−2022.55, 1640.37] and a two-sided empirical probability of 0.8332. Since both intervals cross zero, this study cannot conclude that the dynamic strategy has a significant average cost advantage [21-23].

Table 3. Cross-operation playback results of the main control strategies

Playback direction	Strategy	Total cost of standardization process / × 10^4	Instant satisfaction rate / %	Actual recording box CVaR90/×10^4	Relative B1c cost change / %
MAS1→MAS2	B1c	518.07	97.79	11.22	0.00
MAS1→MAS2	B2	525.87	92.63	12.42	1.51
MAS1→MAS2	Proposed	524.11	93.29	12.36	1.17
MAS2→MAS1	B1c	878.24	98.90	11.51	0.00
MAS2→MAS1	B2	875.63	98.61	13.43	-0.30
MAS2→MAS1	Proposed	875.61	98.79	12.46	-0.30

Cost structure further illustrates this difference. In MAS1→MAS2, Proposed reduces procurement, conversion, and holding costs relative to B1c, but backlog costs increase from 4.23×10^4 to 12.55×10^4, thus failing to create an overall cost advantage. In MAS2→MAS1, Proposed has slightly lower procurement and conversion costs, but higher backlog costs in the tail bin offset this gain. This result is consistent with observations from existing research: a more suitable inventory rule may yield greater benefits than a small improvement in forecast accuracy. In the current sample, B1c's higher procurement buffer has absorbed most of the short-term volatility, and the dynamic strategy has not consistently found a better cost-service mix [24].

5.3 Explanation of Stress Situations and Mechanisms

Figure 1 illustrates the total cost changes of Proposed relative to B1c under the main playback and preset stress scenarios. When the procurement lead time increases from 1 recorder to 2 recorders, the cost of Proposed decreases by 1.16%, the immediate satisfaction rate increases by 0.93 percentage points, and the actual recorder CVaR90 decreases by 1.82%. This scenario shows a consistent improvement. The other five stress scenarios did not yield the same results. When overall sales volume increases by 20%, the cost of Proposed increases by 1.03%, the immediate satisfaction rate decreases by 4.55 percentage points, and the actual recorder CVaR90 increases by 6.85%; when sales volume increases by 40% for AA-F16, the three changes are 1.12%, -4.54 percentage points, and 8.51%, respectively; when the scenario width is increased by 1.25 times, the three changes are 0.42%, -2.00 percentage points, and 6.55%, respectively [25].

When the inventory holding factor doubles, the cost of Proposed increases by 1.03%, the immediate satisfaction rate decreases by 4.52 percentage points, and the actual record box CVaR90 increases by 10.56%. When the backlog factor doubles, the cost of Proposed increases by 2.37%, the immediate satisfaction rate decreases by 4.61 percentage points, and the actual record box CVaR90 increases by 3.43%. These results indicate that Proposed does not provide a stable overall advantage under conditions of high holding costs, high backlog costs, or increased sales volume. The negative values in Figure 1 only indicate that the total cost of Proposed's standardization process is lower and do not necessarily mean that service and tail risk will improve simultaneously.

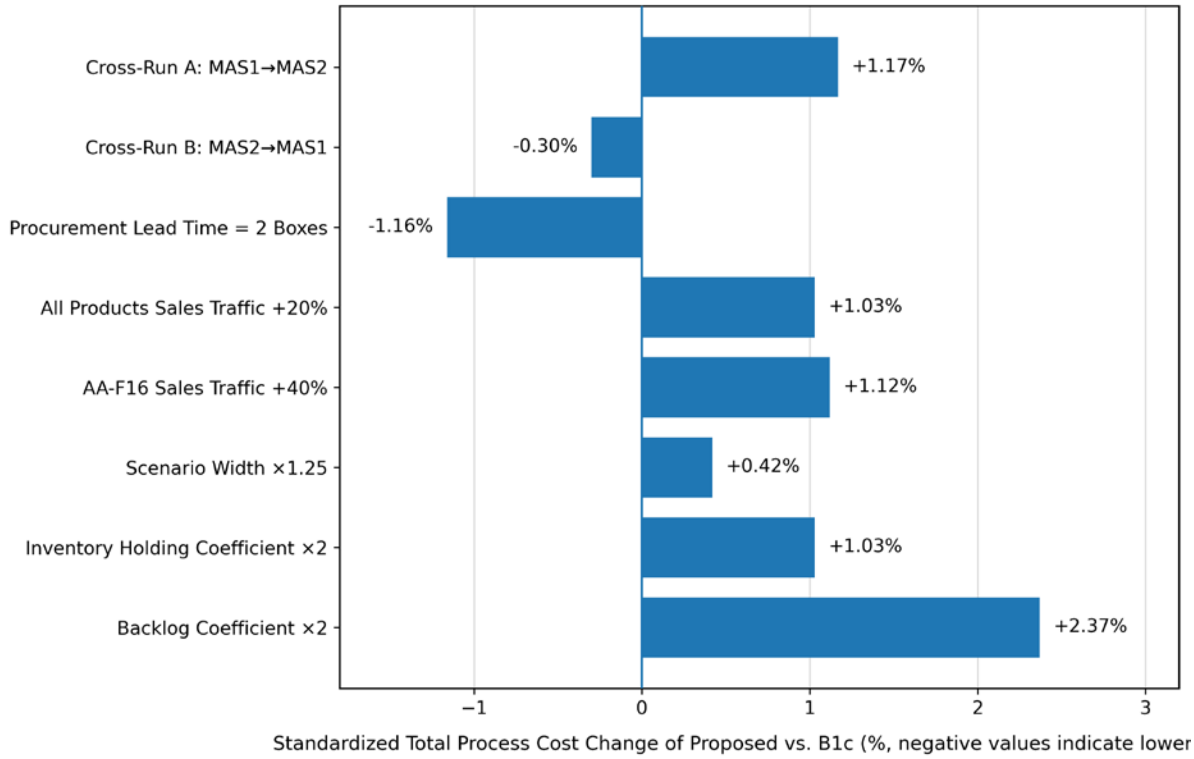

Figure 1. Total cost variation of Proposed relative to B1c under main playback and stress scenarios.

This result does not mean that the proposed risk screening mechanism has failed, but rather that its incremental effect is limited by two conditions. B1c has been calibrated to a high buffer rule through service constraints during the development period, so it can cover most of the sales flow in a short planning period. At the same time, the current scenario CVaR90 is calculated based on the development run residual block and 20 equally probable scenarios, while the actual record box CVaR90 during the test period reflects the tail cost in the real playback, and the two are not the same. Even if the strategy selects a lower risk scheme at the scenario level, it cannot guarantee that it will reduce the tail cost simultaneously under the actual sales flow of another run. In Figure 1, only the scenario with increased procurement lead time shows both cost reduction and increased immediate satisfaction rate; most other scenarios fall in the area of "increased cost and decreased immediate satisfaction rate". Existing rolling supply and demand matching studies have also shown that the effect of dynamic updates depends on the demand status, planning cycle and available capacity.

6. Discussion and Management Implications

of this study is not that "complex algorithms are ineffective," but rather that there is a clear conditional relationship between prediction error, inventory rules, and cost outcomes. QGB's prediction error was lower than the moving average in both cross-run replays, but its advantage was limited. The high-buffered fixed rule showed better overall performance in one set of replays, but in another set, it only traded higher immediate satisfaction and lower tail costs for a minimal cost difference. This phenomenon reminds companies that predictive model updates cannot be directly equated with improved operational performance. The value of complex methods needs to be demonstrated through comparison with well-calibrated operating rules, rather than relying on a weak baseline to amplify differences.

When enterprises carry out cost control, they should include raw material receipt, material requisition, finished product warehousing, sales flow and backlog status in the same ERP analysis chain, and should not judge the source of cost based solely on the financial accounts at the end of the period. Before deploying complex models, enterprises also need to calibrate safety stock and procurement buffers during the development period. When simple rules can stably achieve service goals, enterprises should decide whether to modify the system based on interpretability, maintenance costs and risk boundaries, rather than just pursuing algorithm complexity. When the procurement lead time is extended, the demand structure changes frequently or product fluctuations are significantly amplified, quantile forecasting and scenario control can still be used as auxiliary decision-making tools, but enterprises must simultaneously set service lower limits, end-stage backlog handling and tail cost monitoring. Rolling production and inventory planning under stochastic demand also needs to be tested through multiple scenarios, and should not be judged by a single average cost.

7. Conclusion

This study, based on publicly available normal operation transaction records from ERPsim, constructs a standardized process cost counterfactual simulation framework for the procurement-production-inventory-sales flow after clarifying data boundaries. The study uses rolling quantiles (LightGBM) to generate demand intervals and achieves multi-objective rolling control through 847 sets of shared strategies, service constraints, and scenario CVaR90 filtering. Two online replays across runs show that QGB's P50 prediction WMAPE is slightly lower than the moving average, but still at a high level. Compared to the high-buffered moving average rule calibrated during development, the proposed approach does not show a stable advantage.

In the MAS1→MAS2 transition, the Proposed control is inferior to B1c in terms of cost, immediate satisfaction rate, and actual record box CVaR90. In the MAS2→MAS1 transition, the Proposed control is only 0.30% cheaper, a negligible difference, and has higher tail costs. Under the pre-set stress scenarios, only an increase in procurement lead time resulted in a consistent improvement; other scenarios did not establish a stable dominant trend. This study does not demonstrate that complex dynamic control can universally reduce the overall process cost in the current ERPsim sample. The results further suggest that a small improvement in forecast accuracy does not automatically translate into operational benefits; reasonable service buffers often explain a larger portion of the control effect.

This study has several limitations. The data comes from a serious ERP game, and the sales invoice quantities are merely a proxy for sales flow; the study only covers 3 finished products, 8 materials, and a relatively short operating period; the cost coefficients are standardized parameters. Online replay allows the model to use the history of the released test period, therefore it cannot replace long-term real-world enterprise deployment validation. Future research needs to obtain real orders, inventory, procurement lead times, transportation settlements, and financial costs to examine whether complex controls can generate identifiable incremental value in longer-term and more rule-mismatched environments.

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