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DATA-DRIVEN FEFO-AWARE OPTIMIZATION APPROACH IN WAREHOUSE MANAGEMENT FOR CHEMICAL INDUSTRY DISTRIBUTORS

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ABSTRACT

Warehouse management in chemical distribution companies faces challenges due to high order picking costs and the risk of product expiry. Traditional approaches that prioritize distance efficiency and demand frequency often overlook First Expired, First Out (FEFO) compliance, leading to increased waste and reduced service performance. This study proposes a Data-Driven FEFO-Aware Optimization approach that integrates slotting, robust order batching, and an integrated decision model to enhance warehouse operational efficiency while managing expiration risks. Twelve months of historical transaction data from a chemical distribution company were analyzed, and the proposed models were validated through discrete-event simulation in a warehouse with five storage zones. The study developed three optimization strategies: a FEFO-aware slotting algorithm considering demand, storage efficiency, and remaining shelf life; a robust order batching approach balancing picker travel and expiration risk; and an integrated decision model incorporating SKU relocation costs. Simulation results indicate that FEFO-aware slotting improves operational performance and service level, while FEFO-based batching significantly reduces picker travel and eliminates expiration costs. The integrated model further optimizes overall warehouse efficiency. These findings demonstrate that combining FEFO-compliant slotting and batching decisions provides substantial improvements in operational efficiency, expiration risk management, and service performance.

KEYWORDS: FEFO Compliance, Warehouse Management, Order Picking, Slotting Optimization, Order Batching, Chemical Distribution, Data-Driven Approach.

1. INTRODUCTION

Warehouse system efficiency has become one of the strategic factors in improving the competitiveness of the global supply chain. With the growth of e-commerce, logistics digitization, and increasing customer demand for small and frequent orders, the role of warehouses is no longer just as a storage place, but as an order processing centre that must prioritize speed, accuracy, and flexibility (Yang et al., 2022). In this ecosystem, warehouse management serves as the backbone to ensure that products are available on time, in the right quantities, and at the lowest possible cost.

One of the main challenges in warehouse management is the high cost and complexity of order picking activities. Recent studies show that order picking can contribute 50-75% of total warehouse operating costs (Coyle, 2016). Therefore, optimizing picking strategies, from slotting to batching, has become a major focus in both research and industrial practice.

In the literature, slotting strategies are widely discussed as an important approach to reducing travel distance and picking time. Both the Cube per Order Index (COI) and ABC classification approaches have been proven to improve picking efficiency by placing high-turnover items closer to the pick-up/drop-off point (Duque-Jaramillo et al., 2024). Alqahtani (2023) introduced an Analytic Hierarchy Process (AHP)–based model to address the storage allocation and assignment problem by applying the Cube-per-Order Index (COI) as the basis for ABC classification and organizing the storage area using a class-based policy. While this approach effectively prioritizes operational efficiency through demand-driven criteria, it does not explicitly account for product perishability, in contrast to FEFO-aware storage strategies that integrate remaining shelf life as a key decision factor. However, the majority of these approaches are only oriented towards demand frequency and volume, without taking into account the shelf life of the product. This poses a significant weakness in the context of the chemical industry, especially for consumable products that have a high risk of expiry.

The First Expired, First Out (FEFO) principle, which requires products with shorter shelf lives to be prioritized in distribution, is crucial for chemical distribution companies. Failure to comply with this principle not only has the potential to increase waste and financial losses but can also pose legal and reputational risks to the company. Unfortunately, the integration between data-driven slotting strategies and FEFO mechanisms has not been studied in depth (Zarinchang et al., 2024).

In addition to slotting, order batching strategies are also key to warehouse efficiency. Traditional approaches focus only on reducing picker travel distance, but recent research has developed a data-driven robust batching framework that utilizes historical transaction data to create batches that are more adaptive to demand variations and operational conditions (Bayram et al., 2022). The study shows that a data-based approach can increase daily warehouse capacity by up to 14.8% without requiring machine learning-based predictive technology.

Furthermore, research by Xue & Gao (2024) emphasizes that the batching problem cannot be separated from the packing stage, which is known as the Order Batching and Packing Problem (OBOPP). OBOPP shows that decisions in batch formation will affect workload distribution and potential bottlenecks in the sorting and packing processes. This holistic approach is especially important in the era of modern distribution, when demand variation is high and SLA requirements are increasingly stringent.

Although many studies have examined slotting and batching separately, a research gap remains in integrating the two while considering the dimension of FEFO compliance. Most studies only evaluate operational efficiency in terms of time and cost, but have not systematically linked it to the issues of waste reduction due to expiration and SLA fulfillment in the context of chemical distribution (Duque-Jaramillo et al., 2024; Zarinchang et al., 2024).

Therefore, this study contributes by proposing a Data-Driven FEFO-Aware approach that integrates slotting and batching strategies for chemical distribution companies. This approach utilizes historical transaction data, demand patterns, and product expiry characteristics to develop a more comprehensive operational strategy. The research focuses on three key aspects of warehouse performance, namely: (1) increased throughput, (2) reduction of waste due to expiration, and (3) SLA fulfillment. Thus, this study is expected to expand the academic literature while providing practical recommendations that can be implemented by chemical distribution companies. The research questions used in this study are:

1. Does an increase in the Slotting Score(i) affect throughput improvement, expiry waste reduction, and SLA fulfillment in warehouse management?
2. Does a decrease in the objective function value of Robust Order Batching affect throughput

improvement, expiry waste reduction, and SLA fulfillment in warehouse management?
3. Does a decrease in the objective function value of Slotting-Batching Decision Integration affect an increase in throughput, a reduction in expiry waste, and SLA fulfillment in warehouse management?

The expected research objectives are as follows:
1. Analyze the effect of an increase in Slotting Score(i) on an increase in throughput, a reduction in expiry waste, and SLA fulfillment in warehouse management.
2. Evaluate the impact of a decrease in the objective function value of Robust Order Batching on increased throughput, reduced expiry waste, and SLA fulfillment in warehouse management.
3. Measure the effect of a decrease in the objective function value of Slotting-Batching Decision Integration on increased throughput, reduced expiry waste, and SLA fulfillment in warehouse management.

2. LITERATURE REVIEW

2.1 The Importance of Slotting in Chemical Distribution

Slotting is the process of placing goods (SKUs) in the most efficient storage locations to minimize picker travel distance while speeding up the picking process. Slotting strategies based on ABC classification and Cube per Order Index (COI) have been widely used in warehouse management literature. Duque-Jaramillo et al. (Duque-Jaramillo et al., 2024) showed that integrating COI with specific slot assignment sequences significantly reduced picking time compared to random or simple rule-based approaches. This finding is in line with the research by de Jesus Pacheco (2023) highlighted the effectiveness of ABC classification in mitigating operational waste within distribution warehouse environments. Their study combined multiple conceptual modeling frameworks with a quantitative approach based on successive correlation vectors and matrices to support allocation decisions. The results showed that ABC-based structuring of storage locations contributed to reduced transportation waste during order picking.

However, in the chemical industry, especially for consumable products with limited shelf life, conventional slotting approaches have limitations. Zarinchang et al. (Zarinchang et al., 2024) emphasize that placement decisions should not only depend on demand frequency and item volume but also consider worker safety and the risks of storing hazardous products. In chemical products, placement errors can increase potential risks, both in terms of safety and financially due to damage or expiration.

Therefore, the application of the First Expired, First Out (FEFO) principle needs to be integrated into the slotting strategy so that goods with closer expiration dates can be prioritized for earlier removal. Research by Espinoza-Camino et al. (2020) shows that warehouse management models that use FEFO, 5S, and chaotic storage can significantly improve efficiency. Thus, FEFO-aware slotting is not only a matter of efficiency, but also a crucial risk mitigation strategy in the chemical distribution sector.

2.2 Data-Based Order Batching

Order batching is a strategy of grouping orders into a single batch to be processed at once, with the main objective of reducing picker travel distance and improving work efficiency. The study by Bayram et al. (Bayram et al., 2022) introduces the Robust Order Batching Problem (ROBP), which utilizes historical transaction data to compile optimal batches under fluctuating demand conditions. The results show a time saving of 7-8 minutes per batch, which translates to a 14.8% increase in daily capacity. These findings prove that data-driven batching can provide significant advantages without having to rely on machine learning-based predictive approaches. Other prior research has demonstrated the applicability of data-driven and optimization-based decision models across a wide range of operational contexts, including logistics planning, warehouse operations, order consolidation and batching decisions, as well as dynamic and real-time decision-making environments. These studies collectively illustrate the flexibility of such approaches in addressing complex, high-dimensional operational problems under uncertainty and evolving system conditions (Bertsimas & Stellato, 2021; De Lombaert et al., 2023; Vanheusden et al., 2023).

Then from Wang et al. (2020) proposed a data-driven storage location assignment mechanism that leverages order-related item characteristics to minimize total travel distance in warehouse operations. Their approach generated multiple assignment scenarios based on ABC classification, demonstrating improvements in picking performance through the use of data-informed decision rules. However, while classification methods were shown to be beneficial, they were not treated as a primary strategic mechanism for solving the storage assignment problem.

Furthermore, Xue & Gao (Xue & Gao, 2024) emphasize that order batching cannot be separated from the order packing process, giving rise to the concept of the Order Batching and Packing Problem (OBOPP). In other words, decisions in batch formation must consider the distribution of workload at the packing stage to avoid bottlenecks. This is particularly relevant in the context of chemical distribution, where products handled can vary from perishable consumables to non-consumables that require special handling.

Other recent research has highlighted the growing role of data-driven methods in enhancing both problem approximation and algorithmic decision-making within large-scale optimization. Akkerman and Mes (2025) demonstrated that regression-based estimation models can accurately approximate cost and distance measures in routing problems such as the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP), providing an efficient alternative to analytical approximation formulas. In parallel, Paulus et al. (2022) showed that learning-assisted strategies can improve key algorithmic components, including cutting-plane selection, thereby enhancing solution quality, convergence speed, and computational robustness in complex optimization frameworks. Together, these studies underscore the effectiveness of data-driven approaches in supporting scalable and reliable optimization under high problem complexity.

A data-driven approach allows companies to use historical order patterns, order frequency, and volume variability as the basis for adaptive batching. Thus, a robust data-driven batching strategy can strike a balance between operational efficiency and SLA compliance, ultimately improving customer satisfaction and company profitability.

2.3 FEFO Principle in Inventory Management

The First Expired, First Out (FEFO) principle is a critical strategy in the inventory management of perishable products. Unlike FIFO (First In, First Out), which only considers the order of arrival, FEFO prioritizes products based on their nearest expiration date (Najlae et al., 2021).

FEFO principle is particularly critical in warehouses handling chemical and other perishable inventories, where product degradation, expiration, and regulatory compliance impose strict constraints on storage and picking decisions. In mass-consumption warehouse environments, Figueroa-Rivera et al. (2022) demonstrated that the integration of FEFO within a lean warehousing framework significantly reduces rework, waste, and non-value-added movements by prioritizing items with shorter remaining shelf life during picking operations. Their findings highlight that FEFO-driven storage and picking alignment is especially relevant for products subject to shelf-life limitations and quality deterioration, as it directly mitigates the risk of expiry-related losses and inefficient handling. Moreover, the study shows that FEFO effectiveness increases when combined with standardized processes, layout optimization, and workload balancing, reinforcing its applicability as a robust operational strategy for chemical and perishable inventory management.

In a practical context, FEFO implementation faces several challenges. Mendoza-Villajuan et al. (2024) show that integrating FEFO with SARIMA forecasting and EOQ can improve inventory management in supermarkets. Their research emphasizes the importance of supporting technologies such as RFID and IoT to facilitate real-time tracking of product shelf life. Without adequate technological support, manual FEFO implementation is often ineffective and prone to human error.

2.4 Supporting Technologies in Warehouse Management

Advances in digital technology have opened up new opportunities in optimizing warehouse management. Choy et al. (2017) developed an RFID-based warehouse management system with an integrated fuzzy-decision model that can improve inventory tracking accuracy and reduce picking errors. This technology is particularly relevant for FEFO implementation as it enables real-time tracking of each product's shelf life. Zhong et al. (2022), Huang et al. (2022), and Lesch et al. (2023) proposed mixed-integer nonlinear programming models to jointly optimize order picking and packing operations in e-commerce warehouse environments. Their findings demonstrate, through simulation-based numerical experiments, that integrated modeling yields superior performance compared to sequential or non-integrated approaches. Although comprehensive reviews of integrated warehouse decision problems and their variants have been provided by Boz & Aras (2022), the existing literature remains relatively limited in addressing the joint optimization of picking and packing processes.

Y Wang et al. (2022) developed a storage assignment optimization model based on an Adaptive Genetic Algorithm to minimize item movement and travel distance while enhancing order-picking efficiency. Their approach focused on robotic mobile fulfillment systems operating within a fishbone rack warehouse layout and incorporated factors such as working distance and aisle workload balance. However, the model did not explicitly account for order correlation effects in storage assignment decisions.

Silva et al. (2022) introduced a machine learning–based methodology to estimate the optimal scale of ABC product allocation in warehouse environments. Their approach incorporated key factors such as warehouse layout, demand patterns, and storage and routing policies, and demonstrated performance improvements by comparing ABC-based storage with random allocation strategies. However, the study focused on the Product Allocation Problem (PAP) using ABC as the sole slotting methodology and did not incorporate routing optimization within the decision framework.

The integration of slotting and order picking decisions is widely motivated by the need to streamline operational workflows, reduce picking time, lower picking and storage costs, and improve picking accuracy (Đurđević et al., 2022; Echeverria Garcia & Espinoza Alarcon, 2023; Perron & Furnon, 2022). However, there is no universally optimal combination of slotting and picking strategies, as effective solutions are highly dependent on warehouse characteristics, technological maturity, and order demand profiles (Ghobakhloo et al., 2023). Despite growing interest in integrated warehouse decision-making, the combined use of ABC classification and the Cube-per-Order Index (COI) remains relatively underexplored, indicating its potential to enhance the standardization and performance of integrated slotting and picking strategies, particularly under bulk-handling conditions (Zhan et al., 2022)

3. METHODOLOGY

3.1 Research Framework

This study uses a mixed-methods approach that combines quantitative analysis of historical transaction data with discrete simulations to evaluate the performance of the proposed optimization strategy. The research framework consists of three main stages:

a. Data Collection and Analysis Stage: Collection of 12 months of historical transaction data, including order patterns, product characteristics, expiration dates, and current warehouse performance metrics.
b. Model Development Stage: Development of FEFO-aware slotting algorithms and data-driven batching strategies using machine learning approaches and optimization techniques.
c. Validation and Evaluation Stage: Implementation of models in discrete event simulations and performance evaluation against three KPIs: throughput, expiry waste, and SLA fulfillment.

3.2 Data Collection

Data was collected from the chemical distributor's Warehouse Management System (WMS), including:

a. Historical transaction records (orders, picking, shipping) for 12 months
b. Product master data (dimensions, weight, expiry characteristics, product category)
c. Storage location configuration and warehouse capacity
d. Performance metrics (picking time, error rate, expiry waste)
e. Customer SLA data and fulfillment rates

3.3 Optimization Model Development

The Optimization Model from the data-driven approach to FEFO Optimization refers to factors that can influence increased throughput, reduced expiry waste, and improved SLA fulfillment from warehouse management.

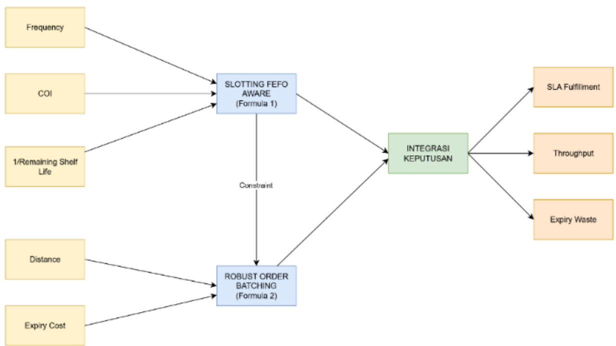

Figure 1. FEFO Optimization Model.

The FEFO-aware optimization model was developed with three interrelated components as illustrated above. Each component consists of factors that influence the FEFO model to be optimal, with the following explanations:

3.3.1 FEFO-Aware Slotting Algorithm

Development of a multi-criteria slotting algorithm that considers demand frequency, product dimensions, and remaining shelf life. The slotting algorithm was developed by combining the Cube per Order Index (COI) and remaining shelf-life indicators. Products with high frequency and short shelf life are placed closer to the picking point. A weighting scheme is used to balance distance efficiency and FEFO compliance. The algorithm uses weighted scoring with the formula:

$$Score(i) = a \times Frequency(i) + \beta \times COI(i) + \gamma \times (1/RemainingShelfLife(i))$$

where α, β, and γ are weights optimized using a genetic algorithm based on historical data.

Table 1. FEFO – Aware Slotting Algorithm Formula Definition.

Components	Definition	Slotting Interpretation
α x Frequency(i)	Require frequently purchased products to be located nearby	Zero-distance priority for high turnover
β x COI(i)	Improve space efficiency by considering size per frequency	Balance between high volume and usage
γ x 1/RSL(i)	Reverse remaining shelf life → the closer to ED, the higher the score	Ensure FEFO in placement

3.3.2 Robust Order Batching Strategy

Implementation of the ROBP approach with FEFO constraints to ensure that batches are formed taking into account efficiency and expiry priorities. The mathematical model is formulated as:

Minimize: Σ(Distance) + λ × Σ(ExpiryCost)

Subject to: Capacity constraints, FEFO constraints, Time window constraints

Table 2. Robust Order Batching Strategy Formula Definition.

Components	Definition	Objectives
ΣDistance	Total travel distance for pickers for one batch	Operational efficiency
ExpiryCost	Penalty function: the closer to expiry → the higher the penalty if the batch is delayed	FEFO compliance
λ	Weighting factor between distance efficiency and expiry risk	Controlling the trade-off between performance and compliance

3.3.3 Decision Integration Module

Development of a decision support system that integrates slotting and batching decisions in real-time based on current inventory status and incoming orders. The system uses event-driven architecture to respond to changes in operational conditions. Slotting and batching decision models are dynamically integrated to produce an FEFO priority sequence that is also operationally efficient. This integration ensures that products nearing their expiration date remain prioritized without sacrificing throughput using the following formula:

Minimize:Z= w1 ∑ DistanceBk(Li) + w2∑ ExpiryCosti + w3 ∑ ReassignmentCost(Li,t)

Table 3. Decision Integration Module Formula Definition.

Symbol	Definition
∑ DistanceBk(Li)	Total picker distance for batch B_k based on slotting results
∑ ExpiryCosti	Increasing FEFO penalties for fast expiry
∑ ReassignmentCost(Li,t)	Slot transfer costs when stock conditions change (event-driven)
W1, W2, W3	Priority weighting: efficiency vs. expiry vs. location stability

3.3.4 Hypotheses and Hypothesis Testing

Based on the theoretical framework and literature reviewed, the research hypotheses are as follows:

H1 — The Effect of Slotting Score(i)

a. H1: An increase in Slotting Score(i) has a positive effect on throughput, expiry waste reduction, and SLA fulfillment.

H2 — Effect of Robust Batching Objective Function

b. H2: A decrease in the value of the Robust Order Batching objective function has a positive effect on increasing throughput, reducing expiry waste, and SLA Fulfillment.

H3 — The Effect of the Decision Integration (Z) Objective Function

c. H3: A decrease in the value of the Decision Integration (Z) objective function has a positive effect on increasing throughput, reducing expiry waste, and SLA Fulfillment.

Hypothesis testing is used to ensure that the research conducted is valid:

Table 4. Hypotheses and Testing Method.

Test Type	Purpose	Decision Criteria
F Test (Simultaneous)	Determine whether all independent variables (Slotting Score(i), Robust Batching, Decision Integration) collectively have a significant effect on each dependent variable (Throughput, Expiry Waste, SLA Fulfillment).	- If p-value < α (0.05), then H_0 is rejected → the model is simultaneously significant. - If p-value ≥ α (0.05), then H_0 fails to be rejected → the model is not simultaneously significant.
t Test (Partial)	Test whether each independent variable (X_1, X_2, X_3) has an individual effect on each KPI (Y_1, Y_2, Y_3).	- If p-value < α (0.05) → H_a is accepted → the independent variable has a significant effect. - If p-value ≥ α (0.05) → H_0 is accepted → no significant effect. - For positive hypotheses → β coefficient is expected

		to be positive. - For negative hypotheses → β coefficient is expected to be negative.
Coefficient of Determination Test (R^2 and Adjusted R^2)	Assessing the extent to which independent variables contribute to explaining variations in dependent variables.	- R^2 value is close to 1 → the model explains the variability of the dependent variable well. - Low R^2 value → small contribution of independent variables to the dependent variable.
Classical Assumption Test (if using parametric regression)	Ensuring that the regression model is suitable for use (normality, multicollinearity, heteroscedasticity, autocorrelation).	- Normality is satisfied (e.g., p-value > 0.05 in the normality test). - No multicollinearity (VIF < 10, Tolerance > 0.1). - No heteroscedasticity (p-value > 0.05). - No autocorrelation (Durbin-Watson approaches 2).

3.4 Simulation and Validation

The developed model was implemented in a discrete event simulation using AnyLogic software. The simulation was designed to replicate actual warehouse operations with the following parameters:

a. Simulation period: 30 operational days
b. Number of SKUs: 100 products with varying expiry characteristics
c. Order volume: 200-300 orders with seasonal variability
d. Number of pickers: 4 operators with 8-hour shifts
e. Warehouse area: 22 m x 115 m
f. Zone division: 5 (A, B, C, D, E)

Validation is performed by comparing the simulation results with actual data using a paired t-test with a 95% confidence level. The model is considered valid if there is no significant difference between the simulation results and actual conditions.

4. RESULTS AND DISCUSSION

The research data used is historical data from company transactions over the last 12 months to obtain the FEFO slotting algorithm that will be used to determine the rank for slotting allocation for products with the lowest expiration date to be simulated so that the slotting placement is in accordance with the expiration date in the zone closest to the warehouse door. The warehouse has 5 zones, namely zones A, B, C, D, and E with illustrations of the zones with the size of the warehouse attached.

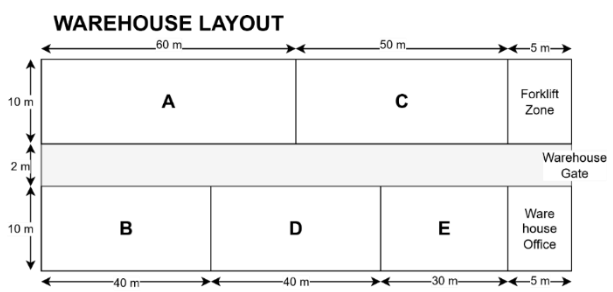

Figure 2. Warehouse Layout Sketch.

It can be seen that the warehouse has 5 storage zones with the following divisions:

Zone A = 60 m x 10 m
Zone B = 40 m x 10 m
Zone C = 50 m x 10 m
Zone D = 40 x 10 m
Zone E = 30 x 10 m

Currently, the division of product placement has not been adjusted according to expiration dates and the calculation of the distance to retrieve items that are nearing their expiration date to be closer to the warehouse door, so that the picking and loading process can be faster and the warehouse can be shipped. Therefore, a simulation was carried out to prove the level of operational efficiency of the warehouse and reduce waste from expired products.

3.1 General description of data and analysis approach

This study uses warehouse operational data from a chemical distribution company with a total of 100 active SKUs and five storage zones (A–E). An optimization model was developed to measure the impact of implementing the FEFO-Aware algorithm on three main aspects of warehouse performance:

a. Operational efficiency (throughput and picker travel distance)
b. FEFO compliance (expiry cost and expiry waste)
c. Service performance (SLA fulfillment)

The performance measurement approach is based on actual indicators with operational units:

a. Throughput: number of orders per day (orders/day)
b. Distance: average picker travel distance per order (meter/order)
c. Expiration Cost: average expiration cost per order (Rp/order)
d. Expiration Waste: percentage of expired stock to total inventory (%)
e. SLA Fulfillment: percentage of orders delivered on time (%)

Simulations were conducted for four conditions: (1) Baseline (existing operations), (2) Slotting FEFO-

Aware, (3) Robust Order Batching (ROBP), and (4) Decision Integration Module (Z).

3.2 Results of the Slotting FEFO-Aware Model

This section presents the results of research on the evaluation of the FEFO-aware slotting model developed using the assessment function in Formula (1). The evaluation was carried out by comparing warehouse operational performance between the baseline condition and the after FEFO slotting scenario, based on the simulation results for four main indicators, namely picking distance, picking time, SLA fulfillment rate, and FEFO compliance

3.2.1 SKU Ranking Results Based on the FEFO-Aware Slotting Model

Based on the results of the evaluation of Formula (1), a slotting score was obtained, which was used to rank all SKUs. This score reflects the priority of placing SKUs in warehouse zones closer to the exit, taking into account the picking frequency, Cube Order Index (COI), and Remaining Shelf Life (RSL).

The ranking results show that SKUs with high picking frequency, low COI values, and shorter remaining shelf life consistently receive higher scores and are prioritized for placement in zones with shorter travel distances. This shows that the FEFO-aware slotting model is capable of integrating operational efficiency and expiration risk control aspects into a single decision-making mechanism.

3.2.2 Impact on Travel Distance and Picking Time

Based on the results of the warehouse physical performance evaluation, the application of FEFO-aware slotting resulted in significant improvements in picking distance and time.

Total picking distance decreased from 19,120 meters in the baseline condition to 16,200 meters in the after scenario, or an efficiency of 15.27%. Similarly, the total picking time decreased from 6,018.13 minutes to 5,759.79 minutes, with an average decrease in picking time per order of 2.62% and an aggregate time efficiency of 4.29%.

These findings indicate that FEFO-aware layout improvements directly contribute to increased operator movement efficiency and order fulfillment speed.

3.2.3 Impact on SLA Fulfillment Rates and FEFO Compliance

Based on the results of research on service quality evaluation and shelf life management, the implementation of FEFO-aware slotting also showed an increase in SLA and FEFO compliance indicators.

The SLA fulfillment rate increased from 62.18% to 82.90%, or an increase of 20.73%. Meanwhile, the FEFO compliance rate increased from 81.386% to 86.733%, with an improvement of 5.347%.

The improvement in these two indicators shows that SKU placement optimization not only has an impact on internal warehouse efficiency, but also improves service reliability and consistency in the application of the FEFO principle.

3.2.4 Final Aggregate Performance of the FEFO-Aware Slotting Model

To obtain a more comprehensive picture of performance, the results of the simulation of the four indicators were then combined into a single aggregate performance index using a weighted average approach. This approach was used to represent the relative contribution of each indicator to the warehouse's operational objectives. The indicator weights were set as follows:

Table 5. Slotting FEFO Weight Indicators.

Indicators	Weight
Picking Distance Efficiency	20%
Picking Time Efficiency	20%
SLA Fulfillment Improvement	30%
FEFO Compliance Improvement	30%

Next, each indicator is normalized in the form of a percentage increase relative to the baseline. Based on the simulation results, the following aggregate values were obtained:

1. Distance efficiency: 15.27%
2. Picking time efficiency (aggregate): 4.29%
3. SLA fulfillment improvement: 20.73%
4. FEFO compliance improvement: 5.35%

Thus, the aggregate performance index is calculated as:

$$\begin{aligned}\textbf{Aggregate Performance Index}\\ &= (0.20 \times 15.27) + (0.20 \times 4.29)\\ &+ (0.30 \times 20.73) + (0.30 \times 5.35)\\ &= \mathbf{11.74}\%\end{aligned}$$

This value shows that, overall, the application of the FEFO-aware slotting model results in an 11.74% improvement in warehouse operational performance compared to the baseline conditions.

Based on the results of the partial and aggregate evaluation, the FEFO-aware slotting model has been proven to provide consistent performance improvements in various dimensions of warehouse operations. Improvements in physical efficiency (distance and time), service quality (SLA), and shelf-life management (FEFO) indicate that Formula (1) functions not only as a SKU ranking tool, but also as a measurable operational optimization mechanism.

With an aggregate performance improvement of 11.74%, the FEFO-aware slotting model can serve as a strong foundation for further integration with the robust order batching strategy (Formula 2) and integrated decision module (Formula 3) discussed in the next section.

3.3 Results of the Robust Order Batching (ROBP) Model

Based on the results of research on the application of the Robust Order Batching (ROBP) strategy combined with the FEFO constraint, a comprehensive picture of the trade-off between operational efficiency and product expiration risk control was obtained. This model is formulated to minimize the objective function consisting of the total travel distance of the picker and the expiration risk penalty, as stated in Equation (2).

Table 6. ROBP Model Indicators and Result.

Performance Indicators	Baseline	After FEFO + ROBP	Changes/Impacts
FEFO Compliance (%)	41,98%	100,00%	+58,02 percentage points
High Expiry Risk Rate (%)	58,02%	0,00%	Expiration risk eliminated
Total Travel Distance (ΣDistance, meter)	159.980	35.350	↓ 77,90%
Estimasi Expiry Cost (Rp)	4.828.773.315	0	↓ 100%
Objective Function Value (Z)*	306.480	35.350	↓ 88,47%

3.3.1 FEFO Compliance Performance and Expiration Risk

The simulation results show that the baseline scenario still has a relatively low FEFO compliance rate of 41.98%, indicating that most orders do not fully follow the principle of picking items based on the shortest remaining shelf life. This condition is reflected in the high proportion of orders with high expiry risk, which reached 58.02% of the total simulated orders.

Conversely, the application of ROBP with FEFO constraints was able to significantly increase FEFO compliance to 100%, where all orders in the after scenario successfully met the FEFO rules. The direct impact of this improvement is the total elimination of orders with high expiry risk, so that the high expiry risk rate drops from 58.02% to 0%. These findings indicate that the integration of FEFO as a constraint in batch formation plays a crucial role in controlling the risk of products that are sensitive to shelf life.

3.3.2 Picker Travel Distance Efficiency

From an operational efficiency perspective, this study evaluated the total picker travel distance based on the formed batch allocation. Under baseline conditions, the total travel distance was recorded at 159,980 meters, reflecting a conventional batching pattern without distance optimization and FEFO priority.

After implementing ROBP integrated with FEFO-aware slotting results, the total picker travel distance decreased dramatically to 35,350 meters. This decrease is equivalent to a 77.90% reduction in travel distance, indicating that a batching strategy that considers storage location proximity and route consistency can significantly improve picker movement efficiency.

3.3.3 Expiry Cost Analysis and Objective Function

To quantify the economic impact of expiry risk, this study uses an expiry cost approach based on the average value per SKU, which is Rp 16,480,455. In the baseline scenario, the number of orders with high expiry risk results in a total estimated expiry cost of Rp 4.83 billion. Conversely, in the after FEFO + ROBP scenario, no orders with high expiry risk were found, resulting in an estimated expiry cost of Rp 0.

By integrating the distance and expiry cost components into the objective function, this study calibrates the weighting factor λ to equalize the expiry risk penalty with the distance operational penalty. The calculation results show that the total objective function value in the baseline condition is much higher than in the after scenario. In aggregate, the objective function value decreased by 88.47%, reflecting the success of ROBP in balancing operational efficiency and FEFO compliance.

3.3.4 Summary of Robust Order Batching Model Performance

Overall, the results of the research on Formula 2 show that:

a. The integration of FEFO as a constraint in robust order batching is able to eliminate the risk of expiration systematically.
b. Optimizing batch formation contributes significantly to reducing picker travel distance without compromising compliance with expiry rules.
c. The objective function that combines distance and expiry cost provides a more holistic evaluation framework compared to conventional batching approaches that only focus on distance efficiency.

These findings confirm that FEFO-based Robust Order Batching is not only relevant for improving warehouse operational efficiency, but also plays a strategic role in controlling risks and costs due to expired products. The results in Formula 2 further form the basis for integration with Formula 3, which combines slotting and batching decisions in a single optimization framework.

3.4 Results of the Decision Integration Model (Z)

Based on the results of research on the integration of FEFO-aware slotting and robust order batching decisions, Formula 3 was developed to evaluate warehouse system performance holistically by considering three main components, namely picker travel distance efficiency, product expiration risk, and implementation costs due to changes in storage location. This model is formulated in a unified objective function that combines these three components through calibrated weighting.

Table 7. Decision Integration Model Result.

Evaluation Components	Baseline	After Integrated Model	Changes/Impacts
Total Travel Distance, ΣDistance (meter)	159.980	35.350	↓ 77,90%
Estimasi Expiry Cost, Σexpiry Cost (Rp)	4.828.773.315	0	↓ 100%
Reassignment Cost, ΣReassignment Cost (Rp)	0	16.480.700	One-time implementation cost
Objective Function Value, Z (meter-equivalent)	306.480	35.850	↓ 88,30%

3.4.1 Evaluation of Integrated Model Performance

The calculation results show that under baseline conditions, the total objective function value reaches 306,480 (meter-equivalent), which is dominated by the contribution of picker travel distance and expiration risk penalties. This high value reflects the limitations of the conventional approach, which separates slotting and batching decisions, resulting in long operating distances and significant exposure to expiration risk.

After applying the integrated model, which combines FEFO-aware slotting results and FEFO-based robust order batching, the objective function value decreased substantially to 35,850 (meter-equivalent). This decrease is equivalent to a reduction of 88.30% compared to baseline conditions. These results indicate that integrated decision-making can produce solutions that are far more efficient and compliant with FEFO principles than partial optimization.

3.4.2 The Role of Reassignment Cost in the Integrated Model

In Formula 3, implementation costs are represented by the reassignment cost component, which reflects the operational effort required to move SKUs from their initial location to their new slotting location. Based on the research results, there were 100 SKUs that underwent storage zone transfers, with an average transfer cost of Rp164,807 per SKU. Thus, the total reassignment cost incurred in the after scenario was Rp16,480,700.

Although this component adds a penalty to the objective function, its contribution is relatively small compared to the benefits gained from reducing travel distance and eliminating the risk of expiration. This shows that the implementation costs are a one-time cost, while the operational and risk control benefits are sustainable, so that overall, the integrated model still provides significant added value.

3.4.3 Analysis of Slotting and Batching Synergy

The results of Formula 3 confirm the existence of a synergy effect between slotting and batching decisions. FEFO-aware slotting plays a role in reducing the average picking distance and improving the accessibility of SKUs with high expiration risk, while robust order batching ensures that batch formation remains efficient without violating FEFO priorities. When both decisions are integrated, the system is able to achieve an optimal balance between operational efficiency, FEFO compliance, and implementation costs.

These findings indicate that integrated optimization yields superior performance compared to sequential approaches, where slotting and batching are optimized separately. Thus, Formula 3 provides a more realistic and applicable decision framework for warehouse management with time-sensitive product characteristics.

3.4.4 Summary of Integrated Model Results

Overall, the results of the research on Formula 3 show that:

a. The integration of slotting and batching can significantly reduce the objective function value, even after considering implementation costs.
b. Expiration risk can be eliminated without sacrificing operational efficiency.
c. The cost of moving storage locations is relatively small compared to the long-term benefits generated.

These results reinforce the argument that the Integrated Decision Model approach is an effective and sustainable strategy for improving warehouse operational performance, particularly in environments with high expiration risk levels. In the next section, these findings will be summarized and analyzed further in the conclusion chapter to highlight the managerial implications and theoretical contributions of the research.

5. CONCLUSION

Based on the research results, the application of the FEFO-aware slotting algorithm (Formula 1) has been proven to improve the suitability of product placement with demand characteristics and remaining shelf life. This approach results in significant improvements in operational efficiency through a reduction in picking distance and increased compliance with the FEFO principle. Simulation results show that slotting decisions that consider demand frequency, cube-per-order, and remaining shelf life provide a solid basis for warehouse operational optimization that is more adaptive to expiration risks.

Furthermore, the integration of robust FEFO-based order batching (Formula 2) shows further performance improvements by balancing distance efficiency and expiration risk control. The implementation of FEFO-prioritized batching successfully increased FEFO compliance to full compliance, while reducing the total travel distance of pickers and eliminating expiry cost estimates. These findings confirm that batching optimization that focuses solely on distance efficiency has the potential to produce suboptimal results if it does not consider the expiry risk dimension.

In the final stage, the Integrated Decision Model (Formula 3), which combines slotting and batching decisions into a single integrated objective function, proved to deliver the best overall performance. Although this model takes into account the implementation cost of SKU relocation, simulation results show that the reduction in operational distance and elimination of expiry risk far outweigh these costs, resulting in a significant decrease in the objective function value. Overall, this study concludes that the FEFO-based integrated approach is an effective and sustainable strategy for improving warehouse operational efficiency while minimizing product expiration risk, particularly in distribution environments with time-sensitive products.

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7. CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

8. DATA AVAILABILITY STATEMENTS

The data used in this study are not publicly available due to confidentiality agreements with the company but may be available from the authors upon reasonable request.

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