

Robust Warehouse Storage Policy Selection under Cost Uncertainty: An Integrated Pareto, Minimax-Regret, and CRITIC-TOPSIS Approach

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ABSTRACT

Warehouse storage-policy selection requires a balance between material-handling distance and the amount of space reserved for inventory. Comparisons based on one pair of cost coefficients can conceal how the preferred policy changes when the relative price of space and handling shifts. This study develops an integrated decision framework combining Pareto dominance, parametric break-even analysis, minimax regret, objective CRITIC weighting, and TOPSIS ranking. Four policies are evaluated for a three-product, four-period warehouse: dedicated three-class storage, two-class storage with fixed area, two-class storage with space consolidation, and one-class shared storage. The procedure first removes dominated policies. When a credible interval for the space-to-handling cost ratio is available, minimax regret is the primary selection rule; CRITIC-TOPSIS is retained as a complementary physical-performance ranking and as a tie-breaker when the regret result is non-unique or the cost interval cannot be specified credibly. At the baseline parameters, the respective total costs are 650, 690, 615, and 630 cost units. The space-consolidating two-class policy reduces total cost by 5.38%, storage area by 9.09%, and one-way travel distance by 2.67% relative to dedicated storage. Pareto screening removes the two dominated alternatives, and the efficient policies have a break-even space-to-handling cost ratio of 8 in the stated unit system. The minimax-regret analysis over the interval 2-12 selects the two-class space-saving policy. CRITIC assigns weights of 0.5014 to storage area and 0.4986 to travel distance; with only two criteria, these weights are equivalent to normalized criterion standard deviations because the common correlation term cancels. TOPSIS ranks one-class shared storage first with a closeness coefficient of 0.6582, followed by the two-class space-saving policy at 0.6223. Across larger benchmark problem sizes, class-based storage achieves average reductions of 4.66-10.63%. The framework provides a reproducible decision rule and a transparent comparison of monetary robustness and physical-performance preferences.

1. Introduction

Warehouses are no longer passive buffers between production and demand. They are operational systems in which layout, storage assignment, replenishment, and order picking interact

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to determine throughput, service reliability, labor requirements, and logistics cost [1,2]. Research on warehouse design and performance evaluation has emphasized the interdependence of strategic design decisions and operational control [3,4]. This systems view remains relevant because a storage policy changes both the physical footprint of inventory and the distance travelled during put-away and retrieval.

The growth of e-commerce and high-variety distribution has intensified the storage-location assignment problem. Warehouses increasingly process small and time-sensitive orders, experience volatile product popularity, and operate under tighter space constraints. These conditions reduce the usefulness of policies selected only from stable average demand. They also increase the value of decision rules that remain interpretable when demand, cost, or capacity assumptions change [5].

Three broad storage policies dominate the classical literature. Dedicated storage assigns each product to a fixed set of locations. Random or shared storage allows any product to occupy an available location. Class-based storage divides products into a limited number of groups, reserves a region for each group, and permits random placement within the assigned region [6]. Class-based storage is therefore positioned between dedicated and fully shared storage. Its main attraction is that it can retain proximity for high-activity products while pooling inventory variability within each class [7,8].

Most class-formation models balance two consequences. Increasing the number of classes tends to improve travel performance because high-activity products can be kept close to the input/output point. Reducing the number of classes tends to improve space utilization because inventories can share capacity. A policy that minimizes travel alone may reserve excessive space, whereas a policy that minimizes space alone may increase handling effort. The operational decision is consequently governed by the relative economic importance of space and material handling rather than by either measure in isolation.

Warehouse research has moved toward integrated and data-driven formulations. Recent studies combine design, storage assignment, routing, simulation, and association information to capture interactions that simpler rules omit [9,10]. Other work has broadened storage decisions to incorporate human and cost considerations [11], item correlations [12], worker safety [13], and production planning [14]. These developments demonstrate that a single performance measure rarely represents the full decision problem.

The same trend is visible in current solution methods. Data-driven simulation has been used to compare storage schemes under dynamic order-picking conditions [15]. Scattered storage models incorporate product turnover [16], large-scale automated systems are addressed with advanced metaheuristics [17], and general storage-assignment models are solved using nested sampling and order-batching approximations [18]. Machine-learning applications are also entering warehouse-management systems, although interpretability and data requirements remain important constraints [19]. Simulation-optimization has further linked tactical storage allocation with operational picking and replenishment performance [20].

1.1 Literature Synthesis

Recent warehouse research uses optimization, simulation, data-driven assignment, and multi-criteria decision-making to represent the interaction between storage capacity, travel effort, product characteristics, and operating constraints. Table 1 summarizes representative contributions and clarifies the position of the present study. The literature shows strong progress in detailed assignment models, but relatively limited integration of transparent economic thresholds, robustness under uncertain cost ratios, and objective MCDM weighting within one policy-selection framework.

Table 1
Summary of representative warehouse storage and decision-model literature

Study	Setting and method	Main decision dimensions	Research position relevant to this study
Boysen <i>et al.</i> [5]	Survey of e-commerce warehousing	Layout, picking, automation, service speed	Establishes the changing warehouse context; does not provide a robust policy-selection rule.
Silva <i>et al.</i> [10]	Integrated storage-location and order-picking optimization	Storage assignment, routing, operating cost	Captures operational interaction, but not uncertain space-to-handling cost ratios.
Chou <i>et al.</i> [12]	Data-driven storage assignment with item correlation	Turnover, item association, travel performance	Improves product placement; does not compare broad storage policies under cost uncertainty.
Diefenbach <i>et al.</i> [11]	Bi-criteria picker-to-parts optimization and Pareto analysis	Picking efficiency, physical strain, cost	Demonstrates non-dominated trade-offs; space and handling uncertainty are not converted into managerial thresholds.
Yerlikaya and Arikan [14]	Production planning, class-based assignment, and TOPSIS	Product attributes, distance, storage efficiency	Integrates MCDM with classification; the alternatives are products rather than storage-policy configurations.
Xu <i>et al.</i> [15]	Data-driven warehouse simulation	Dynamic picking, trajectories, blocking	Represents dynamic behavior; conclusions remain tied to the simulated operating scenarios.
Pawar <i>et al.</i> [16]	Scattered storage for e-commerce fulfillment	Product turnover, picking effort	Addresses flexible placement; does not jointly model monetary robustness and MCDM ranking.
Li <i>et al.</i> [17]	Multi-objective large-scale automated storage assignment	Efficiency, shelf stability, load balance	Provides scalable optimization, but limited interpretability for policy-level managerial selection.
Prusa <i>et al.</i> [21]	ARAS and CoCoSo for in-house storage-location selection	Occupation cost, loading cost, time, distance	Shows the suitability of MCDM for storage decisions; robustness to changing cost structure is not examined.
Cordeau <i>et al.</i> [20]	Integrated storage allocation, picking, and replenishment	Allocation, picking effort, replenishment interaction	Provides detailed integration; the present study adds compact break-even, regret, and objective-weighting rules.

MCDM is particularly useful when the preferred warehouse alternative depends on several non-commensurate measures. Recent applications have ranked storage locations and product classes using compromise methods such as TOPSIS, ARAS, and CoCoSo [14, 21]. CRITIC derives objective weights from criterion contrast and inter-criterion conflict [22], whereas TOPSIS ranks alternatives according to their distance from positive and negative ideals [23, 24]. Their integration is appropriate here because all physical criteria are quantitative and no expert judgments are required.

Despite this methodological progress, a specific limitation remains in warehouse storage-policy selection: existing models generally either optimize a policy under fixed cost coefficients or rank alternatives using physical or operational criteria, but they do not provide a single transparent procedure that (i) removes policies that are physically dominated, (ii) exposes the exact cost-ratio threshold at which the preferred efficient policy changes, (iii) protects the choice against a bounded but unknown cost ratio, and (iv) reports a non-monetary physical-performance ranking without double-counting cost-derived criteria. Consequently, a manager can obtain different recommendations from cost, robustness, and MCDM models without an explicit rule governing which recommendation has decision priority.

This study addresses that limitation through an integrated and fully transparent decision framework. It first screens storage alternatives using Pareto dominance in area and travel distance. It then expresses total cost as a function of the space-to-handling cost ratio, identifies exact break-

even conditions, and applies minimax regret when the ratio is bounded but unknown. In parallel, CRITIC derives objective weights for the primitive physical criteria, and TOPSIS produces a non-monetary compromise ranking. The models are not combined into a single composite score: minimax regret is the primary selection rule when a credible cost-ratio interval is available, while TOPSIS is used as a complementary diagnostic and as a tie-breaker when the regret result is non-unique or the cost interval is unavailable. The objectives are to: (1) determine the efficient storage policies; (2) identify the economic conditions under which each policy is preferred; (3) rank the alternatives using objective multi-criteria weights; (4) compare MCDM, cost, Pareto, and regret results; and (5) examine whether the advantage of class-based storage persists as problem size increases.

2. Materials and Methods

2.1 Problem Setting and Product Data

The warehouse contains three products observed over four planning periods. Inventory levels vary by period, while the average demand rate represents the activity of each product. Product P1 has the highest demand relative to its peak inventory, P2 combines high demand with the largest storage requirement, and P3 has lower demand. These differences create the basic trade-off between proximity and pooled space. Table 2 reports the complete product-level inputs used in the analysis.

Table 2
Product inventory and demand inputs

Product	Period 1	Period 2	Period 3	Period 4	Average demand/period
P1	5	10	15	10	20
P2	25	20	20	20	20
P3	15	10	10	10	5

The product data are evaluated under four storage configurations. DS-3 assigns each product to a separate dedicated class. CB-2F combines P1 and P2 in one class and retains the same total area as DS-3. CB-2S uses the same two-class grouping but consolidates the pooled inventory requirement, thereby reducing the reserved area. SS-1 places all products in one shared class. The class-based formulations follow the established logic of balancing storage-space reduction and material-handling cost [6, 7].

For each policy, two physical outputs are required: reserved area A_i and one-way weighted travel distance D_i . The latter is obtained by multiplying the average demand assigned to a region by the corresponding expected travel distance. The values in Table 3 preserve the same input/output location and travel convention across all alternatives, so the comparison isolates the effect of storage policy.

Table 3
Storage-policy configurations and physical performance

Code	Storage configuration	Area, A_i	One-way distance, D_i	Two-way distance, $2D_i$
DS-3	Dedicated storage, three classes	55	187.5	375.0
CB-2F	Class-based storage, two classes, fixed area	55	207.5	415.0
CB-2S	Class-based storage, two classes, space-saving	50	182.5	365.0
SS-1	Shared storage, one class	45	202.5	405.0

2.2 Cost and Decision Model

Let f denote the cost per unit of reserved storage area and h denote the cost per unit of one-way handling distance. Because a storage cycle includes movement to and from the input/output point, the two-way handling distance is $2D_i$. The total cost of policy i is therefore:

$$C_i(f, h) = fA_i + 2hD_i \quad (1)$$

The baseline comparison uses $f = 5$ and $h = 1$ cost units under the stated area and weighted-distance units. These values reproduce the relative emphasis placed on space and handling in the dataset. To generalize the analysis, define the space-to-handling cost ratio as:

$$\lambda = \frac{f}{h} \quad (2)$$

Since h is positive, dividing Eq. (1) by h does not change the policy ranking. The normalized cost function becomes:

$$\frac{C_i(\lambda)}{h} = \lambda A_i + 2D_i \quad (3)$$

This transformation removes the monetary scale but does not make the ratio in Eq. (2) dimensionless. With f defined as cost per unit area and h as cost per unit of one-way weighted distance, the ratio has units of weighted distance per unit area; correspondingly, Eq. (3) is expressed in weighted-distance units. The same break-even result applies under any currency provided that f and h are defined with consistent physical units. For that reason, all threshold values reported below are interpreted within the stated area and weighted-distance unit system.

A policy j dominates policy k when A_j is no greater than A_k and D_j is no greater than D_k , with at least one strict inequality. A dominated policy cannot minimize Eq. (1) for any positive f and h because another policy is at least as good on both physical measures. Pareto screening is conducted before cost aggregation. This step reduces the alternatives that require sensitivity and regret analysis and prevents a dominated policy from appearing attractive because of an arbitrary normalization or weighting choice.

For each non-dominated policy, Eq. (3) defines a linear function of λ . The policy with the lowest line at a given ratio is the cost-minimizing alternative. The break-even point between policies i and j is obtained by equating their normalized costs:

$$\lambda^* = \frac{2(D_j - D_i)}{A_i - A_j} \quad (4)$$

A positive finite value of λ^* partitions the decision space into handling-cost-dominant and space-cost-dominant regions. The complete policy ranking is also calculated at $\lambda = 2, 5, 8, 10$, and 12 to show how the decision changes on both sides of the threshold.

Break-even analysis assumes that λ can be specified. In practice, future rent, expansion opportunity cost, labor cost, and equipment cost may be known only within an interval $[L, U]$. For policy i , regret at ratio λ is the difference between its cost and the least cost attainable at that ratio:

$$r_i(\lambda) = C_i(\lambda) - \min_j C_j(\lambda) \quad (5)$$

The maximum regret of policy i over the uncertainty interval is:

$$R_i(L, U) = \max_{\lambda \in [L, U]} r_i(\lambda) \quad (6)$$

The minimax-regret policy is the alternative with the smallest R_i . Unlike expected-value analysis, this rule does not require a probability distribution for λ . It protects the decision maker from the largest avoidable cost associated with selecting the wrong policy under bounded uncertainty.

2.3 MCDM Model

The MCDM layer evaluates the four policies using the two primitive physical criteria: reserved storage area and one-way weighted travel distance. Both are cost criteria, so lower values are preferred. Total cost, space cost, and handling cost are deliberately excluded because they are derived from the same two physical measures; including them would duplicate information and could bias the ranking. CRITIC is retained to preserve an objective and extensible weighting structure that can accommodate additional independent criteria in future applications. However, with only two criteria, the CRITIC conflict multiplier is common to both criteria, so the resulting weights reduce algebraically to normalized standard deviations. This special case is acknowledged explicitly rather than interpreted as additional information supplied by correlation.

Let x_{ij} denote the performance of policy i on criterion j , where m is the number of alternatives and n is the number of criteria. CRITIC first converts each cost criterion into a higher-is-better normalized value:

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (7)$$

The contrast intensity of criterion j is represented by its standard deviation:

$$\sigma_j = \sqrt{\frac{1}{m} \sum_{i=1}^m (r_{ij} - \bar{r}_j)^2} \quad (8)$$

The Pearson correlation between criteria j and k measures redundancy or conflict:

$$\rho_{jk} = \frac{\sum_{i=1}^m (r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^m (r_{ij} - \bar{r}_j)^2} \sqrt{\sum_{i=1}^m (r_{ik} - \bar{r}_k)^2}} \quad (9)$$

The CRITIC information content G_j increases when a criterion has strong dispersion and low positive correlation with the remaining criteria:

$$G_j = \sigma_j \sum_{k=1}^n (1 - \rho_{jk}) \quad (10)$$

The objective criterion weight is obtained by normalizing the information content:

$$w_j = \frac{G_j}{\sum_{j=1}^n G_j} \quad (11)$$

TOPSIS is then applied to the original decision matrix. Vector normalization is calculated as:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (12)$$

The weighted normalized performance is:

$$v_{ij} = w_j z_{ij} \quad (13)$$

Because both criteria are minimized, the best ideal contains the minimum weighted values and the worst ideal contains the maximum weighted values. Superscripts B and W denote the best and worst ideals, respectively:

$$v_j^B = \min_i v_{ij} \quad (14)$$

$$v_j^W = \max_i v_{ij} \quad (15)$$

The Euclidean distances from the positive and negative ideals are:

$$S_i^B = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^B)^2} \quad (16)$$

$$S_i^W = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^W)^2} \quad (17)$$

The relative closeness coefficient Q_i is:

$$Q_i = \frac{S_i^W}{S_i^B + S_i^W} \quad (18)$$

A larger Q_i indicates a policy closer to the positive ideal and farther from the negative ideal. The MCDM ranking is compared with the baseline cost, Pareto, and minimax-regret results. This comparison reveals whether the recommendation is stable across monetary and non-monetary decision structures.

The framework follows a sequential higher-level decision rule rather than averaging the outputs of the different methods. Stage 1 applies Pareto screening to all feasible policies and removes dominated alternatives. Stage 2 has two parallel analyses applied to the retained set. The economic branch uses the cost model, break-even analysis, and minimax regret. When management can define a credible bounded interval for the space-to-handling cost ratio, the unique minimax-regret policy is the primary recommendation. The physical-performance branch applies CRITIC-TOPSIS and is used as a complementary diagnostic. If minimax regret produces a tie, or if a credible cost-ratio interval cannot be established, TOPSIS is used to discriminate among the Pareto-efficient policies. The scale-based benchmark assessment is reported separately as evidence about behavior with increasing problem size and does not override the policy-selection rule. Figure 1 summarizes this procedure.

2.4 Scale-Based Assessment

To examine whether the relative advantage of class-based storage persists as the decision problem becomes larger, the scale assessment uses the computational benchmark protocol reported by Muppani and Adil [6]. For each product count $P = 10, 20, 30, 40, 50$, and 60 , ten random problem instances were generated for a 24×30 square-foot warehouse divided into 1×1 square-foot cells, with the input/output point at the center of the 24-foot side. The planning horizon was fixed at 48 periods. Inventory values and total demand were generated from uniform distributions over the ranges 4-9 and 192-432, respectively [6]. Table 9 reports the published best, average, and worst objective values across the ten instances for dedicated and class-based storage. The benchmark

values are used only for the scale-based comparison and are not inputs to the four-policy decision model developed in this section.

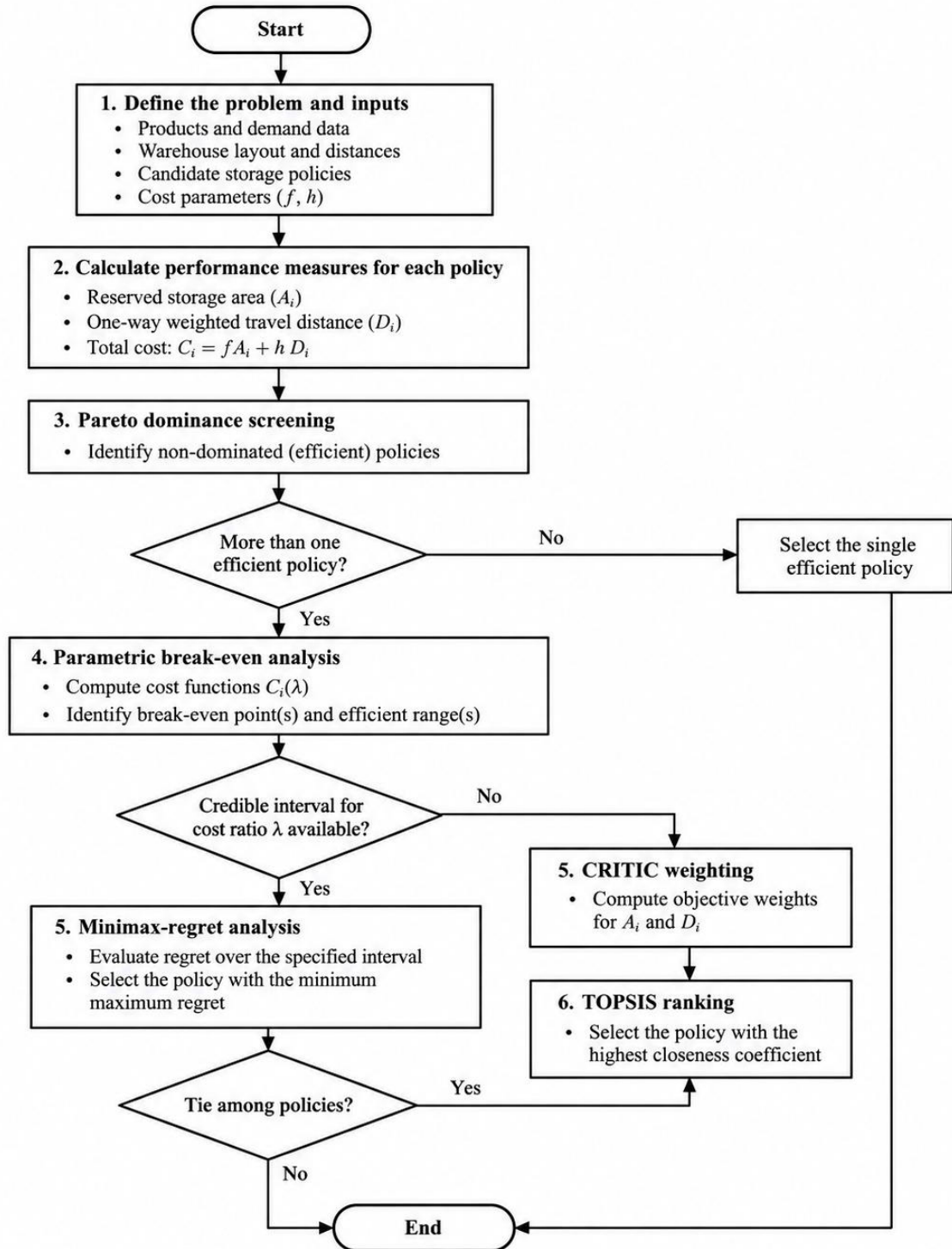


Fig. 1. Integrated decision procedure for warehouse storage-policy selection

$$S_P = 100 \frac{\bar{C}_{D,P} - \bar{C}_{CB,P}}{\bar{C}_{D,P}} \quad (19)$$

The scale analysis is descriptive because only six aggregated problem sizes are available. The mean, median, standard deviation, and linear association between problem size and percentage reduction are reported without treating the six aggregated points as an inferential sample. The average percentage reduction is calculated using Eq. (19). All calculations and figures for the present analysis were produced in Python 3.13.5 using NumPy 2.3.5 and Matplotlib 3.10.8.

3. Results

3.1 Storage-policy performance and Pareto analysis

Table 4 presents the baseline results at $f = 5$ and $h = 1$. CB-2S has the lowest total cost at 615 cost units. Relative to DS-3, it reduces the reserved area from 55 to 50 units and the one-way distance from 187.5 to 182.5 units. The combined effect is a 5.38% total-cost reduction. SS-1 requires the least area, but its longer travel distance raises handling cost; its total cost is 630, corresponding to a 3.08% saving relative to DS-3. CB-2F is the most expensive alternative because it combines the larger travel distance of a two-class arrangement with no space consolidation.

Table 4

Baseline cost and performance comparison at $f = 5$ and $h = 1$

Policy	Area	One-way distance	Space cost	Handling cost	Total cost	Cost saving vs. DS-3	Area / distance change
DS-3	55	187.5	275	375	650	+0.00%	+0.00% / +0.00%
CB-2F	55	207.5	275	415	690	-6.15%	+0.00% / +10.67%
CB-2S	50	182.5	250	365	615	+5.38%	-9.09% / -2.67%
SS-1	45	202.5	225	405	630	+3.08%	-18.18% / +8.00%

The physical comparison yields two non-dominated policies. CB-2S dominates DS-3 because it uses 5 fewer area units and reduces one-way distance by 5 units. CB-2S also dominates CB-2F because it uses 5 fewer area units and reduces one-way distance by 25 units. DS-3 independently dominates CB-2F because both reserve 55 area units while DS-3 has the shorter distance. Therefore, DS-3 and CB-2F cannot be optimal for any positive pair of space and handling costs. The efficient frontier consists only of CB-2S and SS-1.

This result is stronger than the baseline cost ranking. It shows that the space-consolidating two-class policy is not merely cheaper under $f = 5$ and $h = 1$; it is unconditionally preferable to the dedicated and fixed-area alternatives within the two-measure model. The only remaining economic trade-off is between CB-2S, which has the shorter distance, and SS-1, which has the smaller area.

3.2 Cost sensitivity and robust decision

The normalized cost functions are $55\lambda + 375$ for DS-3, $55\lambda + 415$ for CB-2F, $50\lambda + 365$ for CB-2S, and $45\lambda + 405$ for SS-1. Equating the two efficient policies gives $50\lambda + 365 = 45\lambda + 405$, and therefore $\lambda^* = 8$. CB-2S minimizes cost when $\lambda < 8$, whereas SS-1 minimizes cost when $\lambda > 8$. Both policies have a cost of 765 at $\lambda = 8$. Figure 2 shows the four cost functions and the break-even point.

The scenario calculations in Table 5 confirm the analytical result. CB-2S remains the least-cost policy at $\lambda = 2$ and $\lambda = 5$. At $\lambda = 8$, it ties with SS-1. At $\lambda = 10$ and $\lambda = 12$, the area advantage of SS-1 outweighs its additional travel distance. The dedicated policies remain above the efficient frontier throughout the range.

Because the efficient frontier contains two linear cost functions separated at $\lambda = 8$, their maximum regrets have closed forms. For CB-2S, the maximum regret is zero when $U \leq 8$ and $5U - 40$ when $U > 8$. For SS-1, the maximum regret is zero when $L \geq 8$ and $40 - 5L$ when $L < 8$. If the uncertainty interval crosses the break-even point, CB-2S is preferred by the minimax criterion when $L + U < 16$, SS-1 is preferred when $L + U > 16$, and the policies tie when $L + U = 16$.

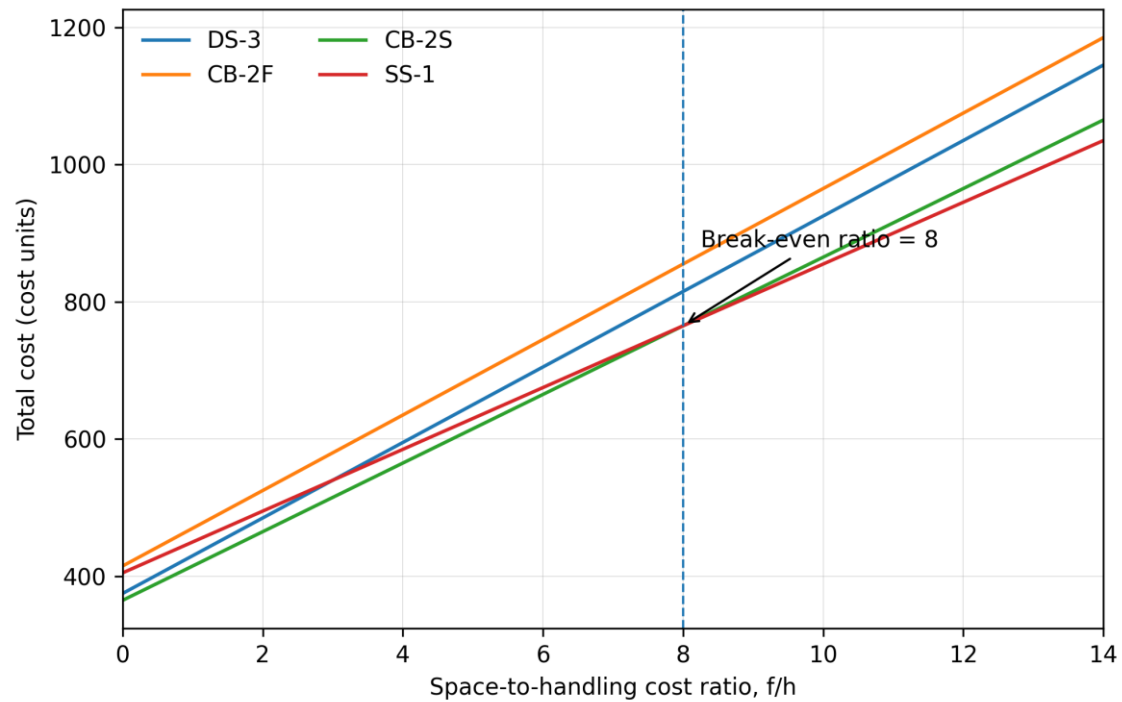


Fig. 2. Total cost as a function of the space-to-handling cost ratio

Table 5

Policy cost under selected space-to-handling cost ratios

$\lambda = f/h$	DS-3	CB-2F	CB-2S	SS-1	Least-cost policy
2	485	525	465	495	CB-2S
5	650	690	615	630	CB-2S
8	815	855	765	765	CB-2S / SS-1
10	925	965	865	855	SS-1
12	1035	1075	965	945	SS-1

Table 6 applies this rule to four bounded ranges. CB-2S is robust when handling costs are important or when the uncertainty interval extends farther below the threshold than above it. SS-1 is robust when the interval lies above the threshold. A balanced interval around $\lambda = 8$ produces equal maximum regret, indicating that non-cost considerations such as congestion, future expansion, product compatibility, or implementation complexity should then determine the final choice.

Table 6

Minimax-regret results for bounded uncertainty in λ

Cost environment	L	U	Max regret: CB-2S	Max regret: SS-1	Minimax selection
Handling-cost dominant	2	7	0	30	CB-2S
Wide mixed range	2	12	20	30	CB-2S
Balanced around threshold	5	11	15	15	CB-2S / SS-1
Space-cost dominant	9	12	20	0	SS-1

3.3 MCDM results and comparison

Table 7 reports the CRITIC calculations. The normalized area and travel criteria have almost identical dispersion. Their correlation is -0.0731. Because there are only two criteria, the factor based on one minus the inter-criterion correlation is identical in both CRITIC information terms and cancels during weight normalization. The reported weights, 0.5014 for reserved area and 0.4986 for one-way

weighted travel distance, are therefore practically the normalized standard deviations of the two normalized criteria.

Table 7

CRITIC objective weights for the physical criteria

Criterion	Preference	Standard deviation	CRITIC information	Weight
Reserved storage area	Lower is better	0.4146	0.4449	0.5014
One-way weighted travel distance	Lower is better	0.4123	0.4425	0.4986

The TOPSIS results are presented in Table 8. SS-1 obtains the highest closeness coefficient, 0.6582, and is ranked first. CB-2S follows closely at 0.6223. DS-3 is third, and CB-2F is fourth because it has the negative-ideal values on both criteria. The two highest-ranked policies are the same alternatives retained by Pareto screening.

Table 8

CRITIC-TOPSIS ranking of storage policies

Policy	Weighted area	Weighted travel	Distance to positive ideal	Distance to negative ideal	Closeness coefficient	Rank
DS-3	0.2682	0.2394	0.0492	0.0255	0.3418	3
CB-2F	0.2682	0.2649	0.0583	0.0000	0.0000	4
CB-2S	0.2438	0.2330	0.0244	0.0402	0.6223	2
SS-1	0.2194	0.2585	0.0255	0.0492	0.6582	1

Figure 3 shows the separation between the TOPSIS coefficients. The narrow difference between SS-1 and CB-2S confirms that neither policy has an overwhelming physical-performance advantage. SS-1 benefits from the smallest area, while CB-2S benefits from the shortest travel distance.

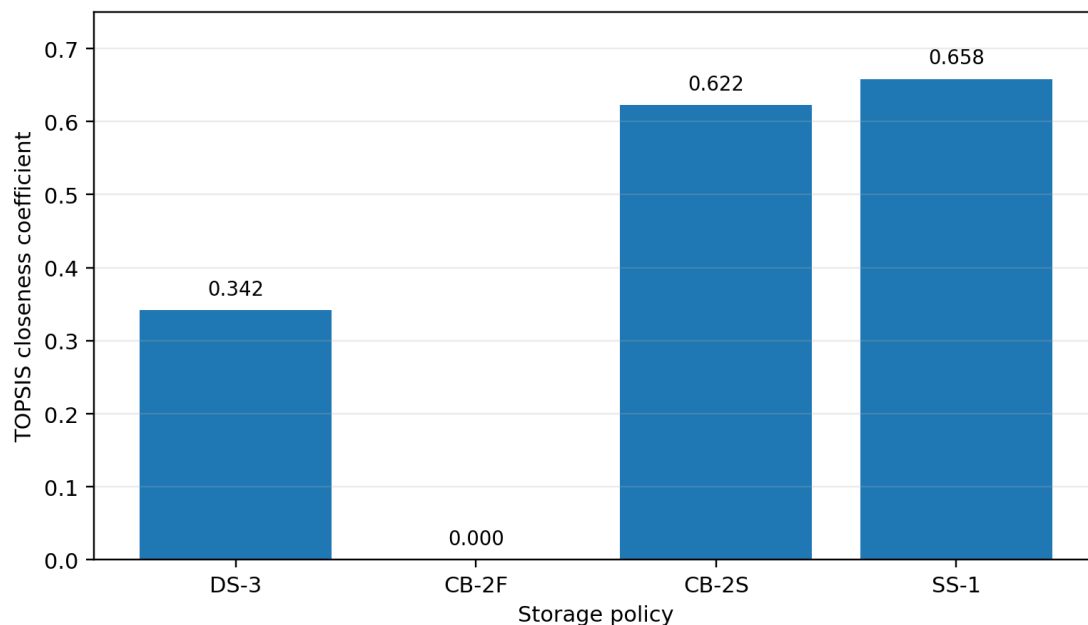


Fig. 3. TOPSIS closeness coefficients for the four storage policies

3.4 Effect of problem size

Table 9 reports the benchmark results generated under the protocol described in Section 2.9 [6]. The class-based policy has the lower average objective value at every product count. The percentage reduction rises from 4.66% for 10 products to 10.63% for 60 products. The mean reduction is 8.41%, the median is 8.62%,

and the sample standard deviation across the six aggregated points is 2.10 percentage points. The descriptive correlation between problem size and percentage reduction is 0.924, with $R^2 = 0.853$.

Table 9

Dedicated and class-based benchmark objective values by problem size

Products	Dedicated best	Dedicated average	Dedicated worst	Class-based best	Class-based average	Class-based worst	Average reduction
10	220.55	220.93	230.31	210.22	210.64	220.14	4.66%
20	620.98	630.49	640.01	570.81	580.92	600.14	7.86%
30	1140.68	1150.69	1160.53	1030.96	1050.91	1080.28	8.67%
40	1740.89	1760.79	1770.91	1590.15	1610.49	1630.18	8.56%
50	2470.08	2480.11	2490.677	2210.796	2230.71	2250.875	10.06%
60	3280.18	3290.17	3300.52	2900.89	2940.39	2970.74	10.63%

Figure 4 presents the same percentage reductions. The gain is not perfectly monotonic: it decreases slightly from 8.67% at 30 products to 8.56% at 40 products. Nevertheless, the overall pattern supports the proposition that pooling opportunities become more valuable as the number of products increases. Larger product sets create more possibilities for offsetting inventory peaks within classes, while dedicated storage must continue reserving capacity product by product.

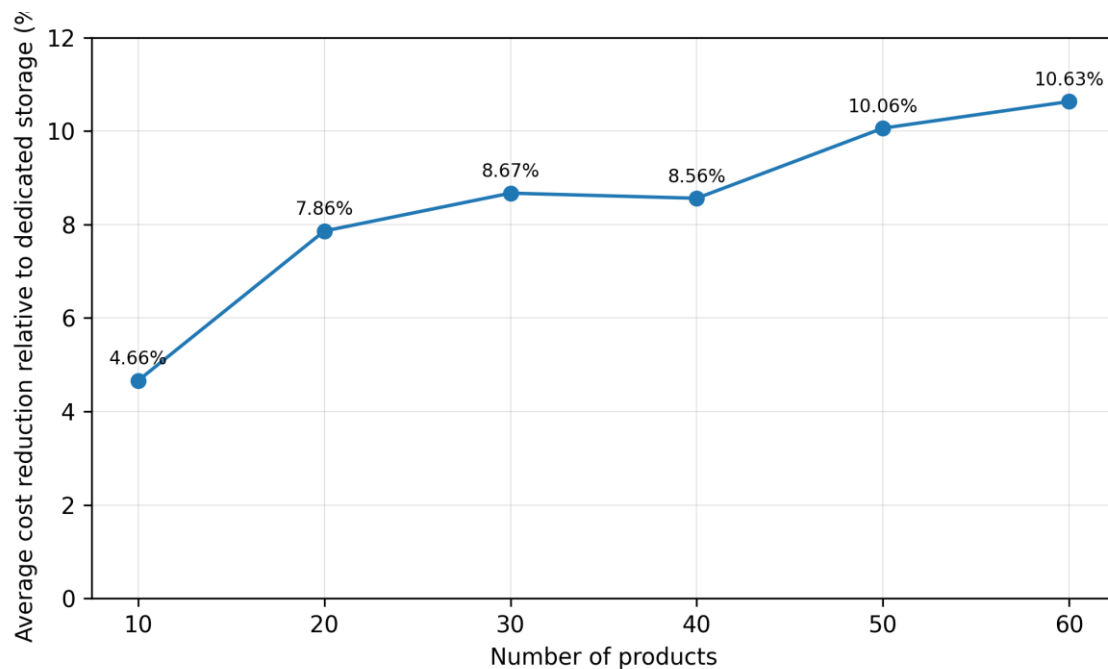


Fig. 4. Average class-based cost reduction as the number of products increases

4. Discussion

4.1 Interpretation of the Findings

The results confirm the central insight of class-based storage research: pooling inventory within a limited number of classes can reduce required area without necessarily increasing travel. Earlier models showed that class formation should account for both storage-space and order-picking costs [6, 7]. The present analysis extends this principle by showing that the choice can be expressed as an explicit economic rule rather than a ranking tied to one fixed cost structure.

The baseline outcome favors CB-2S, but the more important result is its dominance over both dedicated alternatives. DS-3 would often be defended on the basis that fixed locations improve travel performance. In this case, however, the space-consolidating class design achieves a shorter weighted

distance while also reserving less area. This indicates that the inventory-variability benefit of pooling is sufficiently large to move products closer to the input/output point. The result is consistent with studies reporting substantial gains from class-based storage in manual warehouses [8].

The competition between CB-2S and SS-1 is structurally different. Neither policy dominates the other. SS-1 reduces area by a further 10% relative to CB-2S, but increases one-way travel by approximately 10.96%. The break-even ratio $\lambda = 8$ quantifies this trade-off. A warehouse facing high land or expansion opportunity cost should move toward shared storage. A warehouse in which labor, travel time, equipment utilization, or service speed dominates should retain the two-class structure.

Recent storage-assignment studies apply multi-objective optimization [11,17], simulation and data-driven methods [12,15], and MCDM [14,21] to richer operational settings. The integrated result here contributes a complementary level of transparency. Pareto screening establishes physical efficiency, the break-even model converts economic assumptions into an exact threshold, minimax regret addresses bounded uncertainty, and CRITIC-TOPSIS provides an objective compromise ranking. The combined framework makes the source of each recommendation explicit rather than presenting a single unexplained score.

The scale analysis adds a second perspective. The average advantage of class-based storage is positive for every problem size and tends to rise as the product count increases. This supports the expectation that pooled capacity becomes more valuable in larger assortments. The result also cautions against extrapolating from a small warehouse: a policy difference of less than 5% at 10 products expands to more than 10% at 60 products. Storage-policy evaluation should therefore be repeated when the assortment or capacity plan changes materially.

4.2 Comparison of Decision Models

The decision models do not produce an identical first choice, but their roles are now formally separated. Table 10 shows that Pareto screening identifies CB-2S and SS-1 as the only efficient alternatives. Under a credible bounded cost-ratio interval, minimax regret is the primary decision rule; for the interval 2-12 it selects CB-2S. CRITIC-TOPSIS does not override that result. Instead, it provides a complementary physical-performance ranking and becomes the decision rule only when the cost interval cannot be specified credibly or when minimax regret is tied. Under TOPSIS, SS-1 ranks first by a small margin. DS-3 and CB-2F remain inferior under every approach.

Table 10

Comparison of storage-policy recommendations across decision models

Decision model	Primary recommendation	Second result	Interpretation
Baseline cost, $f = 5$ and $h = 1$	CB-2S	SS-1	Diagnostic baseline at one specified cost pair; not the primary rule under bounded uncertainty.
Pareto dominance	CB-2S and SS-1	DS-3 and CB-2F are dominated	Mandatory screening stage; only efficient policies proceed to the selection stage.
Minimax regret, ratio in [2, 12]	CB-2S	SS-1	Primary selection rule when the bounded cost-ratio interval is credible.
CRITIC-TOPSIS	SS-1	CB-2S	Complementary physical ranking; decision rule only for a regret tie or unavailable cost interval.

The difference is substantively useful rather than contradictory because the methods answer different questions. TOPSIS is compensatory and evaluates proportional closeness to an ideal physical profile; it does not convert area and travel into monetary consequences. Minimax regret instead asks

which Pareto-efficient policy limits the largest avoidable cost over a credible bounded ratio. Accordingly, when the interval 2-12 is accepted, CB-2S is the framework's primary recommendation. SS-1 is the TOPSIS preference and would become the operational recommendation only if the cost-ratio interval were unavailable, if the regret result were tied, or if management explicitly chose a physical-performance rather than monetary-robustness decision basis.

4.3 Managerial Implications

The managerial procedure follows Figure 1. First, area and travel measures are calculated for feasible storage configurations using a consistent layout and routing convention. Second, dominated configurations are removed. Third, space and handling costs are estimated and the break-even and regret analyses are performed. Fourth, when a credible bounded cost-ratio interval is available, the unique minimax-regret policy is selected as the primary recommendation. Fifth, CRITIC-TOPSIS is used to report the physical-performance ranking and to resolve a minimax tie or a situation in which the cost-ratio interval cannot be specified credibly. This hierarchy prevents the decision maker from informally switching between conflicting rankings after the results are known.

The ratio λ should include more than contractual rent. The space component may include building depreciation, utilities, expansion opportunity cost, and the value of capacity reserved for future products. The handling component may include labor time, energy, vehicle wear, congestion effects, and the service cost of longer order cycles. Omitting these elements can bias the ratio and move the decision across the threshold.

A policy change also has implementation consequences. Shared storage requires reliable location control, accurate inventory records, and disciplined warehouse-management-system use. Class-based storage requires periodic recalculation of product classes as demand changes. Dedicated storage is easier to recognize physically but can create underused locations. The economic threshold should therefore be interpreted together with the organization's information quality and ability to maintain dynamic location records.

4.4 Limitations and Future Research

The study has four main limitations. First, the cost model contains two aggregated components and does not explicitly represent congestion, replenishment, product compatibility, service-level penalties, or relocation cost. Second, the core policy model uses three products and four periods, which supports transparent derivation but limits the variety of assignment patterns. Third, CRITIC is applied to only two primitive physical criteria and four alternatives; in this special case its weights reduce to normalized standard deviations, so the principal value of retaining CRITIC is methodological consistency and extensibility rather than correlation-based discrimination. Fourth, the scale comparison uses published aggregate benchmark results for ten random instances at each problem size rather than complete instance-level observations, which limits independent distributional analysis.

Future research can extend the framework in several directions. A multi-period version can include relocation cost and switching thresholds between policies. A stochastic version can estimate expected regret when cost distributions are available. Simulation can generate independent criteria for congestion, replenishment, service level, and labor exposure. Hybrid objective-subjective weighting can also combine CRITIC with expert-based BWM when managerial preferences are available. Finally, rank-stability analysis can test TOPSIS under alternative criterion weights and compare it with non-compensatory methods.

5. Conclusions

This study developed an integrated framework for selecting among dedicated, class-based, and shared warehouse storage policies. The method combines physical Pareto screening, parametric cost analysis, minimax regret, objective CRITIC weighting, and TOPSIS ranking. At the baseline cost structure, the two-class space-saving policy achieves the lowest total cost of 615 cost units and improves both area and travel performance relative to dedicated storage.

Pareto analysis shows that the dedicated three-class policy and the fixed-area two-class policy are dominated. The decision therefore reduces to two efficient alternatives: CB-2S and SS-1. Their exact break-even ratio is 8. Minimax regret over the interval 2-12 selects CB-2S, while CRITIC assigns nearly equal weights to area and travel and TOPSIS ranks SS-1 first with a closeness coefficient of 0.6582, narrowly above CB-2S at 0.6223.

The main contribution is an interpretable decision hierarchy rather than a collection of parallel rankings. Pareto screening first defines the efficient set. If a credible bounded cost-ratio interval is available, minimax regret provides the primary policy recommendation; CRITIC-TOPSIS remains a complementary physical-performance assessment and a tie-breaker when the regret result is non-unique or the cost interval cannot be specified. The framework therefore identifies the economic switching threshold, limits regret under bounded uncertainty, and still reports the policy closest to an objectively weighted physical ideal. This structure supports periodic re-evaluation when rents, labor costs, equipment costs, product mix, or managerial priorities change.

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Author Contributions

Conceptualization, I.B.; methodology, I.B.; validation, G.D.; formal analysis, I.B.; writing-original draft preparation, I.B.; writing-review and editing, G.D.; visualization, G.D. The authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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