CHEMICAL ENGINEERING TRANSACTIONS

VOL. 121, 2025

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov

ISBN 979-12-81206-22-9; **ISSN** 2283-9216

DOI: 10.3303/CET25121020

Evaluation of Indirect Storage Location Systems by Fuzzy Signature

Miklós Szabó*, Zoltán A. Nagy, Tamás Hartványi

Department of Logistics and Forwarding, Széchenyi István University, 9026 Győr, Egyetem tér 1., Hungary
szabo.miklos@sze.hu

Traditional storage systems often rely on direct access storage locations, but these solutions can be inefficient and environmentally exhausting due to higher energy consumption and limited scalability. In previous studies, we demonstrated that higher efficiency could be achieved with indirectly-accessible storage systems compared to fully directly accessible ones. To compare the different layouts, we developed a simulation model through which warehouse operations were executed. The resulting time values became comparable, allowing us to rank the solutions. However, the conventional method of calculating simple averages, often applied in the evaluation of logistic performance, has limited capacity to capture the complexity of data distributions and the small differences between individual observations. The aim of this study is to interpret warehouse operations from a new perspective using a fuzzy logic-based model, explicitly addressing the research gap that traditional statistical averages cannot adequately capture subtle performance differences. The novelty of our contribution lies in applying fuzzy signatures to warehouse simulation, which enables more precise differentiation between competing system layouts. During the simulation analysis, traditional average values are compared using a classification method based on fuzzy sets, demonstrating that this new approach is more sensitive to performance fluctuations and better reflects real operational conditions. This approach supports the selection of the most suitable storage system for warehouse operations, the initial placement of products, or the operational process that best aligns with emerging demands, enabling greater energy savings and enhancing the overall sustainability of the system.

1. Introduction

Achieving sustainability requires the optimization of logistics processes, including the operation of warehouses. Warehouses carry out activities that involve significant energy consumption and material handling, which can have considerable environmental impacts. By improving operational efficiency – through automation, modern storage systems, and smart inventory management – it is possible to reduce environmental burdens, minimize waste, and lower carbon emissions. Sustainable warehouses contribute to the responsible use of resources and can also provide a competitive advantage for companies. In our research, we examine how various factors influence warehouse operational performance. Following a review of the relevant literature, we present and analyze the results of simulations based on a model developed from a real-life case study, clarifying how our approach contributes to both sustainability and operational decision-making.

2. Literature Review

2.1 Sustainability in Warehousing

The sustainability of warehousing systems is receiving increasing attention, as the logistics sector has a significant environmental footprint on a global scale. Reducing warehouse energy consumption and CO_2 emissions is not only a cost-saving measure but also a strategic objective in the spirit of environmental responsibility. Solutions aimed at improving energy efficiency include automation, optimization of lighting and climate control systems, streamlining picking routes, and implementing modern warehouse layouts (Ferraro et al., 2023). The concept of sustainable logistics also encompasses management approaches that enhance

Paper Received: 29 June 2025; Revised: 25 August 2025; Accepted: 5 November 2025
Please cite this article as: Szabó M., Nagy Z.A., Hartványi T., 2025, Evaluation of Indirect Storage Location Systems by Fuzzy Signature, Chemical Engineering Transactions, 121, 115-120 DOI:10.3303/CET25121020

resource efficiency and safety, leading to reduced waste and lower operational impacts (Vasileva et al., 2023). Integrating sustainability considerations into warehouse design and operational decisions remains a complex optimization task that must balance economic, environmental, and social factors.

2.2 Indirect Access (Drive-in/Drive-through) Racking Systems and Efficiency

Warehouse layout is a key factor in optimizing space utilization and material handling costs. Indirect access racking systems – such as drive-in or drive-through configurations – offer storage solutions without direct access to every item. Products are stored in multiple layers and rows, which enables excellent volumetric utilization but limits accessibility. The trade-off between direct and indirect accessibility is a critical decision: deeper racking systems reduce aisle lengths and transport distances but increase the number of handling operations, as products located deeper must be moved and replaced to access them (Gue and Meller, 2009). When evaluating warehouse efficiency, it is essential to consider the volumetric utilization, energy consumption, and service times associated with various racking types (Baker and Canessa, 2009).

2.3 Material Handling Strategies and Product Placement Logic

Storage strategies can be optimized by considering product turnover frequency, access time, and proximity to other items. Previous studies (Roodbergen and Vis, 2006) have shown that jointly optimizing layout and handling logic can lead to significant time and energy savings. In indirect racking systems, careful planning of retrieval order and replenishment operations is especially important, as these often require multiple handling steps (Baker and Canessa, 2009). Some researchers have applied metaheuristic algorithms and machine learning methods to address product placement challenges (Albers and Kuper, 2019). More recent studies have extended these concepts: Chen and Li (2024) optimized storage location assignment in human–robot collaborative systems, while Yerlikaya and Arikan (2024) integrated production planning with class-based storage assignment using a multi-criteria approach, both confirming that advanced product classification significantly improves operational efficiency.

2.4 Simulation and Performance Evaluation Using Fuzzy Logic

Simulation models are essential tools for evaluating warehouse system performance, as they allow for testing various layouts, rules, and scenarios without the risk or cost of real-world disruptions. Traditional performance metrics include minimizing average service time or material handling costs. However, these simple indicators may not reflect the complexity of system behavior, such as stability under different environmental conditions or uncertainty captured by data variability. Fuzzy logic enables the handling of uncertainty and vague categorization in performance evaluation. Recent studies demonstrate that fuzzy modeling can enhance the interpretation of simulation outputs and improve decision-making accuracy in logistics networks (Aminpour et al., 2023). In industrial applications, fuzzy-based performance evaluation can be particularly useful for ranking alternatives and supporting decision-making, as it can be combined with expert rule systems and intuitively communicated to stakeholders (Herrera et al., 2000). Current research on warehouse performance focuses mainly on layout optimization, product placement, and simulation-based evaluation. However, most studies rely on mean-based metrics, which fail to capture subtle performance differences, especially in indirect-access systems. Fuzzy approaches have been proposed but rarely applied to full simulation data distributions. This paper addresses these gaps by introducing a fuzzy signature-based evaluation to better differentiate warehouse configurations and support sustainability-oriented decision-making.

3. Model Description

Warehouse performance is influenced by several key factors: the layout and design of the facility, the placement and distribution of products, and the execution of operational processes.

3.1 Model Basis

The case study is based on a real-world raw material warehouse within a manufacturing facility, where a drive-in racking system is implemented. Due to the size of the warehouse and the diversity of stored raw materials, homogeneous storage is not feasible. However, a notable simplification is that all storage units are of uniform size, and none of the materials have expiration dates; adhering to the FIFO principle is not required. The average storage utilization fluctuates around 80 %. For each stored material, the expected quantity, standard deviation, and the assumption of a normal distribution are known. The inventory follows the Pareto principle, meaning that the majority of stored volume corresponds to a small portion of item codes, while most item codes account for a relatively small share of the total volume. This distribution is illustrated in Figure 1. The model includes a total of 99 item codes. Based on turnover rates, the raw materials were grouped into five categories: Group A contains a single item code, accounting for approximately 35 % of the total movement. Each of the remaining groups contributes 14–17 % of the total turnover. Group B also contains one item code, Group C includes 3 codes, Group D has 9, and Group E consists of 85 item codes.

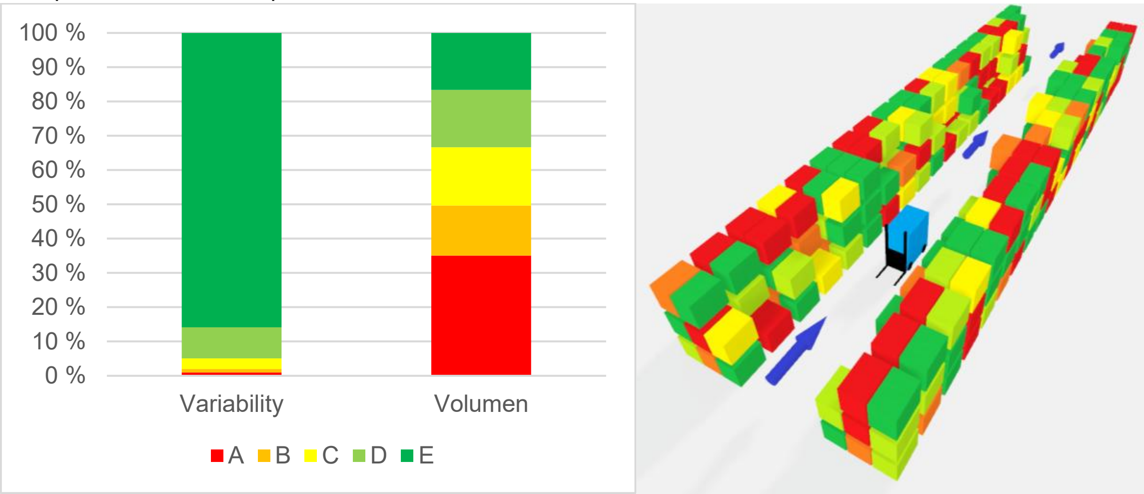

Figure 1: Goods in warehouse model (a) Bar chart illustrating the Pareto principle; (b) Visualization of a randomly generated layout for the 3-deep warehouse configuration

3.2 Warehouse Layout

The material flow in the warehouse follows an I-flow pattern, meaning goods are received on one side and dispatched from the opposite side. In the presented model, the static storage capacity is 360 pallet units. Three different layout configurations were simulated. All three follow an I-flow setup and feature symmetrical arrangements, meaning the central aisle divides the warehouse into two equally deep blocks. Each configuration uses drive-in racking systems with a uniform height of three pallet levels. The only differences lie in the rack depth and aisle length:

- Layout 1 has racks two pallets deep, resulting in an aisle length of 30 pallet positions.
- Layout 2 uses a depth of three pallets, with a 20-position aisle.
- Layout 3 features a depth of four pallets and a 15-position aisle.

If the racks were only one pallet deep, direct access to every item would be ensured. However, this would significantly increase transport distances and reduce volumetric efficiency. Since this study focuses on the potential benefits of indirect access systems, no simulation was conducted for a direct-access layout.

As rack depth increases, the likelihood of a desired item being initially inaccessible also rises. At the same time, shorter aisle lengths reduce transport distances and increase volumetric utilization. While minimizing handling time is a valuable optimization goal on its own, volumetric efficiency adds another layer to decision-making. Ultimately, the cost of material handling must be weighed against the cost of space to evaluate these layout options.

3.3 Material Placement

The second factor influencing performance is how materials are placed within the warehouse. We tested four different placement strategies:

- Strategy 1 is based on ABC analysis: item codes are sorted by turnover and placed near the exit. Because similarly ranked items are positioned perpendicular to the aisle, we refer to this as the perpendicular layout.
- Strategy 2 also uses ABC analysis but ranks items by accessibility rather than absolute distance from the exit. As a result, high-turnover items are placed parallel to the aisle rather than perpendicular to it.
- Strategy 3 follows a method described in an earlier paper (Szabó et al., 2022). For each warehouse layout, we evaluated 1,000 randomly generated placements and selected the best-performing ones. We chose 1,000 iterations because this sample size provides a sufficiently high probability of obtaining at least one outlier, which in turn makes the procedure reproducible. These are referred to as randomized layouts. Figure 1b shows the randomized placement for the three-pallet-deep layout, using the same color coding for item groups as in previous figures. Blue arrows indicate material flow direction.
- Strategy 4 relies on a specific evaluation model that assesses how well each layout matches item accessibility with turnover probability. Unlike standard ABC analysis, this method distinguishes between

multiple instances of the same item code based on their position in the accessibility ranking. It refines the ABC approach by integrating this ranking detail, treating each storage location individually. For this reason, we refer to this as the computationally optimized layout.

3.4 Material Handling Processes

The third factor influencing warehouse performance is the material handling strategy, specifically, how decisions are made about where to place incoming goods and which stored item to select for retrieval. During retrieval, the system always selects the item that enables the task to be completed in the shortest possible time. However, when replenishing stock, different strategies can be used to decide where to store the incoming item.
Although previous studies tested eight clearly defined handling strategies (Szabó et al, 2024), this study focuses on the three most relevant ones:

- Fast handling strategy: Incoming items are placed in the location that allows the current task to be completed in the least amount of time, disregarding any other considerations. This approach does not take into account how the placement affects the accessibility of other items. It provides the quickest execution in the short term and requires minimal computation, making both the operation and simulation highly efficient. We refer to this as the fast strategy.
- Single-channel strategy: This method evaluates how an item's placement affects accessibility within its specific racking channel, selecting the most favorable option from the available positions. It does not consider item turnover probabilities, nor does it take into account the availability of the same item type elsewhere in the warehouse. Since it makes decisions based only on local conditions within a single channel, we call it the single-channel strategy.
- Complex strategy: This approach uses the same evaluation model described in the computationally optimized layout strategy. It selects storage locations by analyzing item turnover and the accessibility of all materials already stored across the entire warehouse. This strategy requires significantly more computation – potentially thousands of times more than the others – but offers a more informed and globally optimized decision. As it follows the same logic as the previously described optimized placement method, we refer to it as the complex strategy.

By combining the three warehouse configurations, four initial placement strategies, and three handling strategies, we created 36 unique simulation setups, each of which was evaluated through simulation.

3.5 Model Operation

Differences between these setups become apparent through their operation. Simulation outcomes are strongly influenced by the nature of the tasks the warehouse must perform. To avoid the pitfall of optimizing for a single example – potentially leading to trivial or misleading conclusions – multiple task sequences must be evaluated under each strategy. Since the aim of the study is to develop long-term, sustainable solutions, the length of the sequences is also a key consideration.
Our earlier research showed that after approximately 3,000 tasks, simulation results begin to stabilize. In this study, each simulation setup was tested using 100 task sequences, each consisting of 3,000 tasks. Each task involved either placing a specific product in the warehouse or retrieving an item based on its product code.
Task execution followed the operating rules of the storage system: deeper items could only be accessed if all items in front of them were first removed. After retrieval, those items had to be returned to ensure no gaps remained in the channel. However, at the front depth level, items were accessible from any vertical position.
Simulations continued based on the changes caused by each task. At the beginning of each new task sequence, the warehouse was reset to its initial state. While the duration of each material handling sub-process was considered deterministic, the task sequences were stochastic. To ensure comparability, the same task sequences were executed across all simulation setups. The execution time of each task was recorded for post-simulation analysis.

4. Results Evaluation

4.1 Time Histograms

To visualize the results, histograms were generated showing how many tasks were completed within specific time intervals. Since the raw counts alone carry little meaning, each value was divided by the total number of simulated tasks in the model, yielding the proportion of tasks falling into each time range. This is illustrated in Figure 2. The time axis in Figure 2 is segmented into 5 s intervals; however, for clarity, the labels are not shown at this level of detail. The final interval includes all values exceeding 270 s.

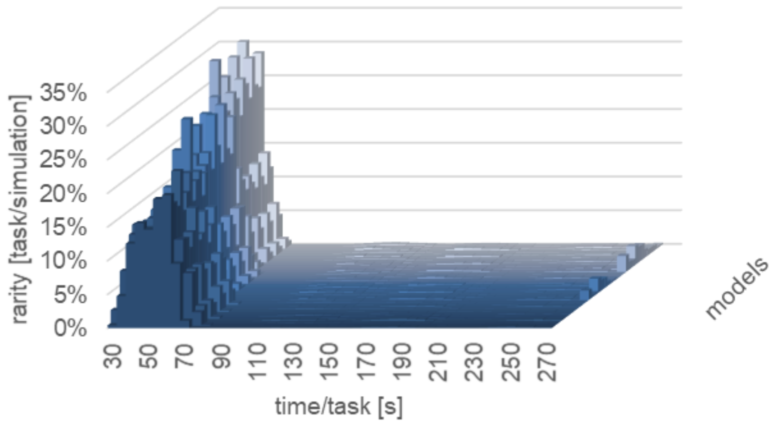

Figure 2: Histogram of observed task durations per model during simulation

4.2 Statistical Analysis

Simulation outcomes were compared using several key statistical indicators: mean, standard deviation, minimum, median, and maximum, as well as derived metrics. The model labeled Simulation 24 achieved the lowest average task time. This scenario involved 3-deep storage blocks, with materials arranged using a calculated layout strategy and operated using the complex handling strategy.

Although two other models performed slightly better in terms of standard deviation, when applying the central limit theorem to estimate the expected duration of 18 tasks during a typical shift, this model still delivered the most favorable results, regardless of whether we consider two, three, or six times the standard deviation.

An interesting observation is how closely the calculated fuzzy values correspond to these performance indicators, reinforcing their validity in evaluating system efficiency. Due to space limitations, however, a detailed discussion of why certain layouts and strategies outperform others could not be included here.

4.3 Fuzzy Evaluation

To account for the large sample size and to reflect the presence of outliers, multiple fuzzy numbers were defined. Based on the simulation results, piecewise fuzzy numbers were constructed using percentiles, keeping the extreme values as boundary points. Percentile thresholds were selected because they provide a robust and widely accepted way to capture distribution tails; sensitivity checks confirmed that alternative thresholds (e.g., 20th–80th) produced qualitatively similar rankings. These fuzzy sets were divided into 100, 10, and 4 intervals, where values were linearly decreased as they moved away from the central mean.

An extreme case of this approach is the asymmetric triangular fuzzy number, consisting of only two segments. Additionally, two trapezoidal fuzzy numbers were defined with breakpoints at the 25th–75th percentile and the 10th–90th percentile.

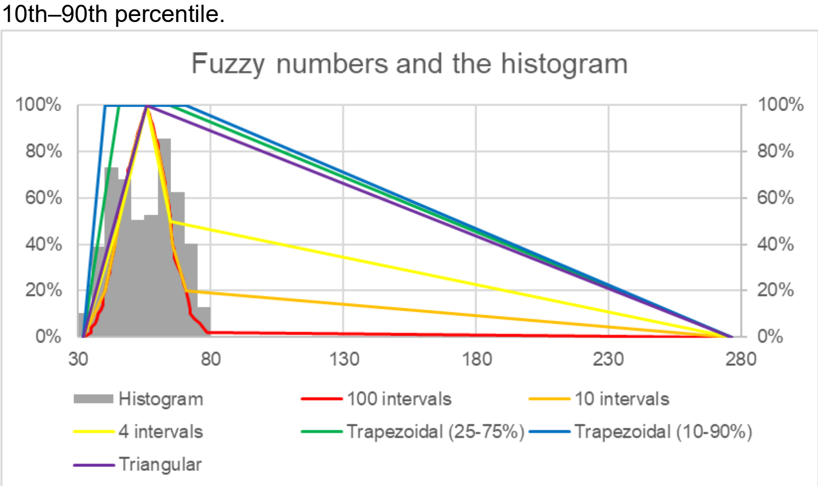

Figure 3: Histogram of observed task durations per model during simulation

Figure 3 illustrates all six fuzzy number shapes overlaid on the histogram of Model 3 (which features 2-deep blocks, materials arranged using perpendicular ABC classification, and operated using the complex handling strategy), and it also clarifies the distinction between Strategy 4 and the complex handling strategy.
The fuzzy numbers obtained were compared across models using a center-of-gravity ranking. This comparison revealed differences compared to the rankings based solely on mean and standard deviation. When the fuzzy number was divided into 100 segments, Model 3 proved to be the most favorable. For all other fuzzy number definitions, Model 9 ranked highest. Model 9 also uses 2-deep storage blocks and the complex handling strategy, but its initial material placement followed a randomized layout. Correlation analysis between the fuzzy-number centroids and the statistical indicators shows that the 100-segment fuzzy number exhibits a very strong correlation with both the statistical evaluation and the other fuzzy numbers (91-95 %). By contrast, the other fuzzy numbers are almost perfectly correlated with each other, but their correlation with the statistical evaluation is only 66-87 %.

5. Conclusion and Future Work

This study presented a methodology for analyzing warehouse operations, considering multiple layout configurations, initial material placements, and operational strategies. Each configuration was simulated, and the results were evaluated using statistical analysis and fuzzy-number–based evaluation, allowing for model-to-model comparison.
Due to space limitations, only the best-performing models were highlighted, and the evaluation methods were compared in general terms. Future investigations could provide deeper insight into the individual influence of each factor on overall warehouse performance. Additionally, further research could determine which evaluation method is most suitable for different operational scenarios. The study may also be extended by developing additional configurations, potentially revealing new optimization opportunities for sustainable warehousing.

References

Albers S., Kuper J., 2019, Metaheuristics for storage location assignment: A survey. Computers & Industrial Engineering, 130, 282–297.
Aminpour S., Irajpour A., Yazdani M., Mohtashami A., 2023, Presenting a fuzzy multiobjective mathematical model of the reverse logistics supply chain network in the automotive industry to reduce time and energy. Discrete Dynamics in Nature and Society, 2023, 8548196.
Baker P., Canessa M., 2009, Warehouse design: A structured approach. European Journal of Operational Research, 193(2), 425–436.
Chen H., Li H., 2024, Solving the Storage Location Assignment of Large-Scale Human–Robot Collaborative Order-Picking Systems for Improved Efficiency. Sustainability, 16(5), 1742.
Ferraro S., Cantini A., Leoni L., De Carlo F., 2023, Sustainable Logistics 4.0: A Study on Selecting the Best Technology for Internal Material Handling. Sustainability, 15(9), 7067.
Gue K.R., Meller R.D., 2009, Aisle configurations for unit-load warehouses. IIE Transactions, 41(3), 171–182.
Herrera F., Herrera-Viedma E., Verdegay J.L., 2000, Direct approach processes in group decision making using linguistic OWA operators. Fuzzy Sets and Systems, 79(2), 175–190.
Roodbergen K.J., Vis I.F.A., 2006, A survey of literature on automated storage and retrieval systems. European Journal of Operational Research, 194(2), 343–362.
Szabó M., Nagy Z.A., Hartványi T., 2022, Random allocation effect on storage performance. Acta Technica Corviniensis – Bulletin of Engineering, 2022(3), 21-24.
Szabó M., Nagy Z.A., Hartványi T., 2024, Storage Location Assignment in Indirect-Access Storage Systems. In: Tamás P., Bányai T., Telek P., Cservenák Á. (Eds), Advances in Digital Logistics, Logistics and Sustainability . CECOL 2024. Lecture Notes in Logistics. Springer, Cham, Switzerland, DOI: 10.1007/978-3-031-70977-7_10.
Vasileva A., Lazarevska A.M., Jakimovska K., 2022, Appropriate criteria for a transition from conventional to sustainable warehousing. Logistics, Supply Chain, Sustainability and Global Challenges, 13(1), 19-31.
Yerlikaya M., Arikan E., 2024, A Novel Framework for Production Planning and Class-Based Storage Location Assignment: Multi-Criteria Classification Approach. Heliyon 10(18), e37351.