Warehouse Layout Design Maximization of Storage Efficiency Minimization of Travel Distances Using Simulation Models and Optimization Algorithms

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Abstract: The issue of warehouse layout design is one of the main decision problems, which has a great influence on the efficiency of operations, cost-effectiveness, and service quality in the logistic system of the modern world. This study offers full-fledged research that utilizes a simulation-based optimization solution to structure warehouse layouts with the aim of maximizing the utilization of the available storage space and the reduction in the travel distances of materials. The paper incorporates the use of class-based policies of storage location assignment and closest open location strategies regarding a variety of storage levels and dynamic inventory mobility. A model simulation of discrete events was created to compare different layouts taking into consideration stochastic change of the production rates, demand patterns, and material handling operations. The optimization model uses a mix of analytical models and metaheuristic algorithms to identify optimal values of aisles, cross aisles, bay depths, and configuration of the storage classes. The computational experiments based on real warehouse data prove that the proposed method has substantial advantages when compared to traditional layout methods and can save the total travel distances by up to 32% without depleting storage space utilization up to 85%. The study adds a closed-form solution to the finding of the optimal aisle numbers, a multi-objective optimization model balancing the competing layout goals, and useful principles to warehouse design decision-making. Findings suggest that effective location of cross-aisles, accompanied by smart location assignment of storage, provide significant operation cost savings. The established methodology offers evidence-based layout design decisions in the form of quantitative tools to warehouse managers and logistics planners, which apply to the wide range of types of warehouses and operational environments.

Keywords: *Warehouse Layout Optimization, Storage Location Assignment, Travel Distance Minimization, Simulation-Based Optimization, Class-Based Storage Policy, Block Stacking Warehouses, Material Handling Efficiency, Space Utilization Maximization, Cross-Aisle Configuration, Discrete-Event Simulation, Metaheuristic Algorithms, Logistics Operations Management, Warehouse Design Algorithms, Order Picking Optimization, Inventory Management Systems.*

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I. INTRODUCTION

A. *Background and Context of Warehouse Layout Design Problems*

➢ *Evolution of Warehouse Design Challenges in Modern Supply Chains*

Warehouse operations are considered the core elements of modern supply chain management systems that are critical nodes, around which inventory storage, order fulfillment, and distribution processes are centred. The growing complexity of the global logistical chain has made warehouse design not only tactical but also strategic which has a direct impact on the competitiveness of the organization (Roodbergen & Vis, 2009). Contemporary warehouses are to fit a wide range of products portfolios, changing patterns of demand, and high service level needs at a cost-effective level. The classical method of developing warehouse plans with the major focus

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on the available space and the principles of intuitive warehouse layouts have not been sufficient to cope with these complex issues (Van Gils et al., 2018). Organizations are now realizing that there are significant operational benefits because of systematic, analytically-based layout design methods. Moreover, the globalization of the supply chain has escalated the level of competitive pressure forcing organizations to maximize all in the operations of the warehouse (Heragu et al., 2006). Also, technological innovations have led to emerging opportunities of automation and optimization of warehouse allowing complex design methodology to be more accessible and useful to practitioners.

The physical layout of storage areas, aisles and material handling routes in the warehouse facilities has severe impact on various performance aspects. Derhami et al. (2020) revealed that the design of layout decisions affects the efficiency of space utilization and the cost of material handling and forms complicated trade-offs that need to be optimized cautiously. The improper design layouts lead to high travelling distance of order pickers, low throughput capacity, and poor utilization of cubic space of available storage space (Le-Duc & de Koster, 2005). Such inefficiencies will grow over the years creating enormous operation costs that deplete profit margins. Besides, inefficient layouts restrict operational flexibility, which restricts the capacity of the warehouse to respond to dynamic business demands (Accorsi et al., 2014). This has led to the development of warehouse design as an important area of research being studied by both the academicians and industry players. Combination of operations research approaches and real-life applications in warehouses resulted in a wide variety of innovations in the layout optimization methods (Manzini et al., 2015).

The design opportunities of warehouse planners are broad, not only due to the technological advances in the material handling equipment, but also in the information systems and automation. By employing automated guided vehicles, advanced warehouse management systems, and real-time tracking technologies, all these make the operations of a warehouse to be more dynamic and efficient (Chen et al., 2011). Nevertheless, the complexity of design increases as well with these technological abilities, and a close attention should be paid to the equipment specification, operation policy, and layout designs. Simulation modeling combined with optimization algorithms are effective tools in analysing design options and finding the best design (Caron et al., 2000). The computational methods allow exploring large design spaces systematically and quantifying performance trade-offs and make informed decisions (Kachitvichyanukul and Sooksaksun, 2012). The integration of operational research models with experimental warehouse design is an important breakthrough in the engineering of the logistics systems.

➤ *Fundamental Components and Design Variables in Warehouse Layout Configuration*

The layout design of warehouses involves a variety of decision variables that are interrelated to each other and jointly define the characteristics of operational performance. The key structural components are storage points, picking aisles, cross-aisles, receiving and shipping docks and material handling pathways. All the parts have operational purposes but have an impact on the efficiency of a system (Heragu et al., 2006). Storage locations are the basic building blocks in which inventory is kept physically with dimensional properties, property of accessibility and capacity limitations (Kovács, 2011). Space utilization is directly proportional to the layout and density of storage facilities, which impact the maximum volume of inventory that can be stored with the space of the available facilities. Increased storage density will enhance space efficiency at the cost of accessibility and material handling efficiency. In addition, the vertical aspect of storage should be taken into consideration because multi-level arrangements allow adding enormous volumetric capacity without raising the area of the facilities (Derhami et al., 2020)

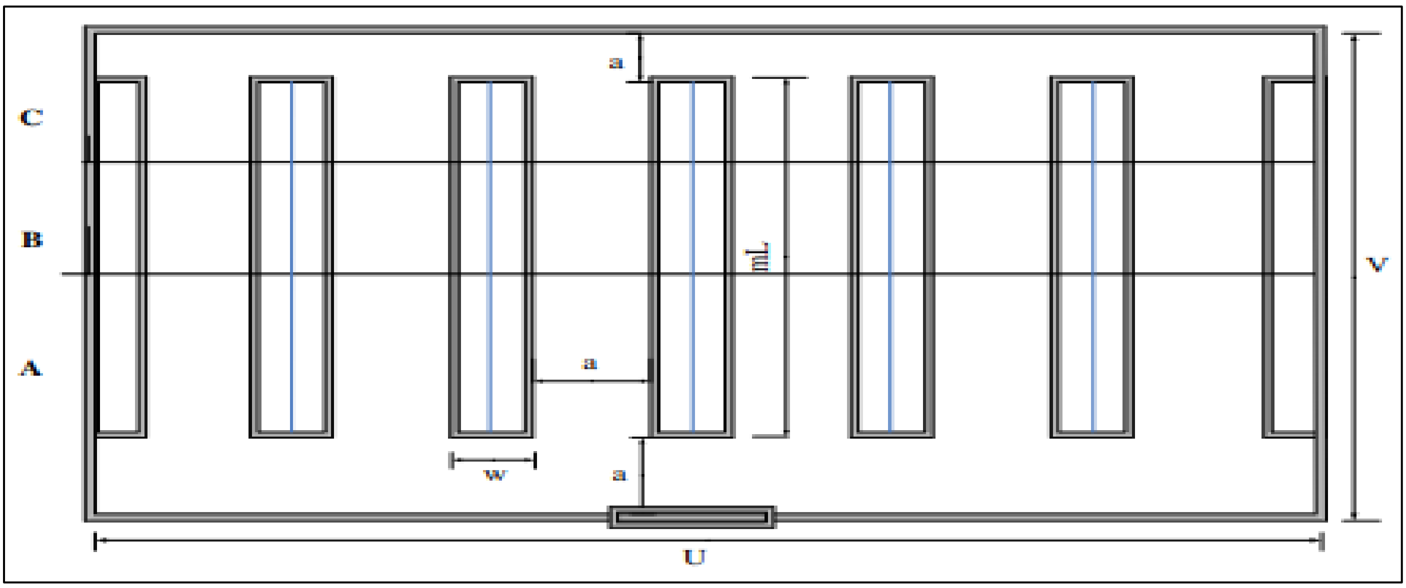

Fig 1 A Cross-Sectional View of the Warehouse Depicting the Parameters.

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Figure 1 shows a cross-sectional diagram of a warehouse that represents the main parameters and location of the relationship among the storage elements. The cross-section of the warehouse presents the working layout of the storage shelves in relation to various classes (A, B, C), the aisle width (a), the height size (h), and the total length (L) and width (U) of the warehouse. This geometrical model shows the combination of dimensional parameters to establish storage capacity and accessibility properties. The figure explains that warehouse design must be considered simultaneously with both allocation of horizontal and vertical space, were aisle widths trade-off between accessibility and storage density. Moreover, creation of different classes of storage shows operation policies where high-turnover products are placed in strategic positions (Muppani and Adil, 2008).

Another important design aspect that has far-reaching effects on the performance of the warehouse is aisle configuration. Aisles offer access ways that allow material handling equipment to access storage areas where inventory can be replenished as well as where the order picking process can be undertaken. Aisles orientation, width, length, and number lead to some basic trade-offs between accessibility and storage capacity (Lee et al., 2020). The wider aisles make the equipment easier to manoeuvre and improve the flow of traffic but use valuable floor space, which can be used to make storage locations (Pohl et al., 2009). The length of aisle influences the travel distances where longer aisles might require more time to travel but have a smaller number of aisles. The best aisle design will be based on various items such as the size of the warehouse, the detailed equipment, and the needs of the operation (Derhami et al., 2020). Analytic models prove that the optimal aisle numbers can be computed by the equalization between the accessibility waste and honeycombing waste in block stacking systems. On the same note, the aisles orientation with reference to input/output points also has a tremendous influence on the average travel distances and the throughput efficiency (Heragu et al., 2006).

Cross-aisles are perpendicular aisles that cut across primary storage aisles to give shortcuts that make material handling operations take shorter travel distances. This may significantly reduce the average travel distance especially in large warehouse facilities with vast storage facilities since the cross-aisles are strategically positioned (Pohl et al., 2009). Nevertheless, cross-aisles occupy more floor space and can be a source of congestion at the intersection points where equipment routes cross (Chen et al., 2011). The number, location and directional nature of the cross-aisles are major design variables that need to be optimized. Unidirectional cross-aisles have less space requirements and can create performance restrictions, whereas bidirectional cross-aisles have more routing freedom and require more space usage (Derhami et al., 2020). The interplay between aisle configuration and cross aisle placement results in complicated dependencies which require combined optimization strategies.

➤ *Performance Metrics and Optimization Objectives in Warehouse System Design*

The optimization of the design of warehouse layout must have well-established performance measures that can measure the effectiveness and efficiency of operations. The two main goals used in deciding on the layout are the need to have maximum use of storage space and reduce the material handling travel distances. Space utilization is the ratio of the total capacity of a warehouse to the amount of capacity used to store inventory without including unused capacity because of accessibility and operational limitations (Derhami et al., 2020). Increased space use helps organizations to store more inventory in the current buildings, and its deferrals or cancelation of expensive facility construction efforts (Fernando et al., 2021). Nevertheless, too much attention to space density will affect the operational efficiency of the system, as it will make retrieval times longer and decrease the system throughput. Besides, the computation of space utilization needs to consider not only the area of the floor but also the vertical cubic capacity of the vertical, understanding that the multi-level storage systems have the capacity to improve (Viveros et al., 2021).

Travel distance is one of the main origins of material handling expenses and warehouse system productivity. All storage and retrieval activities involve the use of material handling equipment to cover the distances between the receiving docks, storage zones, and shipping sites. The total distance that equipment covers in all given operations defines the labor needs, the equipment usage, the energy usage, and the throughput capacity (Le-Duc and de Koster, 2005). By reducing the travel distances, warehouses will be able to handle more orders with the same number of resources, which will enhance cost efficiency and the service quality (Quintanilla et al., 2015). The travel distances greatly depend on the layout configurations because they have on the distance of storage locations relative to the input/output points and the efficiency of the pathways. Adequate placement of high turnover products in areas of shipping and maximization of aisle networks lead to significant reduction of the average movements (Muppani and Adil, 2008).

Table 1 Table of Notation

Notation	**Description**
l	Width of the double shelf
m	Length of a storage space (pallet)
n	Number of the total storage spaces along a shelf
g	Number of the storage spaces allocated to class $i$items
s	Number of double shelves in a warehouse cross-section
K	Total warehouse capacity in the storage spaces
d	Width of an aisle

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W	Length of the whole warehouse
L	Length of each shelf
H	Yearly throughput of the warehouse, in storage units
P_k	Probability of an order belonging to class $i$items
C_h	Material handling cost of moving an item per unit length
T_c	Total travel distance in vertical axis
T_w	Average travel distance in horizontal axis
T_h	Average travel distance in height axis

Table 1 presents the comprehensive notation system employed throughout this research, defining parameters, decision variables, and performance metrics essential for mathematical model formulation. The table systematically categorizes warehouse dimensional parameters including shelf width (l), storage space length (m), allocated spaces (n), total capacity (K), and geometric dimensions (d, W, L, H). Operational parameters encompass yearly throughput (d), order probabilities (P), and material handling costs (C_h, T_c). Additionally, performance metrics including horizontal travel distance (T_w) and vertical travel distance (T_h) are defined precisely. This notation framework enables unambiguous mathematical formulation of optimization models and facilitates clear communication of analytical relationships (Önüt et al., 2008). The standardized notation also supports model extensions and comparisons with related research in warehouse optimization literature.

Additional performance measures complement these main goals, and they give a detailed assessment of quality of layout. The time of order fulfillment is a measurement of time spent on picking tasks, and it depends on the distances of journeys, congestions, and operational policies (Matusiak et al., 2014). Throughput capacity is the measure of the maximum volume of orders that can be processed in definite periods of time that is limited by the material handling resources and layout efficiency. The measures of labor productivity determine the efficiency of human or equipment usage, which is influenced by the complexity of the operations and travelling needs (Battini et al., 2016). Storage accessibility is used to measure ease of access on the stored items based on aisle set-up and density. Operational flexibility is used to determine how well the layout can support changing needs, which is influenced by the policy of assigning storage and physical layout (Glock and Grosse, 2012). Such multi-objectives usually contradict each other and would necessitate multi-objective optimization methods to find Pareto-optimal solutions of the best trade-off arrangements (Önüt, 2008).

B. Storage Location Assignment Policies and Operational Strategies

➢ *Classification and Characteristics of Storage Assignment Policy Alternatives*

Storage location assignment policies are those policies that define the way the incoming inventory is assigned to certain storage locations within the warehouse facilities. The policy choice is essentially a critical operational choice in that it dictates both the space utilization as well as the efficiency of material handling (Muppani and Adil, 2008). The literature on warehouse practice and research literature is dominated by four main types of assignment policies, namely dedicated storage, random storage, closest open location, and class-based storage. Both approaches have different operational philosophies and produce typical performance profiles (Kovács, 2011). Dedicated storage allocates definite storage points to products, which is used to have consistent positioning and ease in the retrieval process. This policy allows tracking inventory and optimizing the storage of a product specific but generally gives a poor space utilization as the reserve capacity gets wasted because of the allocated product being loaded but was not consumed. It provides the predictability of dedicated storage which makes training of order picking easy and saves time of searching of location, but the space inefficiency usually overrides these benefits of operation (Heragu et al., 2006).

The random storage policies allocate incoming inventory to any available storage area, which is randomly chosen among vacant locations. This would maximize the use of space as unused but reserved spaces are removed and more inventory is packed into the available space (Kovács, 2011). Nevertheless, random assignment does not offer any systematic attempts to reduce the travelling distances, which may result in the frequent items being placed in distant areas which are not as close to the shipping locations (Quintanilla et al., 2015). The policy streamlines the process of making assignments but can lead to a non-optimal performance of operations. Closest open location policies place the incoming inventory in the closest available storage space of the receiving docks or specific input points. The inventory is focused on entry points resulting in the possibility of decreasing the average traveling distances with a high space usage (Xiao & Zheng, 2010). However, the nearest open location strategies can cause congestion around entry points, and might not consider the turnover nature of products, and can result in imprecise placement of low turnover products near desirable locations.

Class-based storage is an intermediate solution which features the merits of both dedicated and random policy, and alleviates the drawbacks of each. Products are either grouped according to turnover rates or the frequency of orders or other pertinent aspects (Kachitvichyanukul and Sooksaksun, 2012). Each class is assigned specific warehouse areas, and the classes with high turnover are placed in the ones nearest to shipping docks (Muppani and Adil, 2008). There is random or close open location assigning products in each assigned zone. This policy offers a good level of space usage but in a systematic way of reducing travelling distances of often used products. It has always been proven that class-based policies

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are more effective than the other methods in a wide range of warehouses (Le-Duc and de Koster, 2005). The ability to position products in strategic classes allows a significant reduction in distances travelled as compared to random policies and space efficiency is much better than dedicated strategies. Also, the systems on classes offer flexibility in operations through dynamic within-zone assignment without losing strategic positioning benefits (Zhou et al., 2016).

➢ *Mathematical Formulation of Class-Based Storage Location Assignment Models*

Mathematical optimization models provide formal frameworks for determining optimal storage location assignments under class-based policies. The fundamental objective involves minimizing total material handling costs while satisfying storage capacity constraints and operational requirements. Let c denote storage classes indexed $c = 1,2,\ldots,C$, l represent storage locations indexed $l = 1,2,\ldots,L$, and p indicate products indexed $p = 1,2,\ldots,P$. The binary decision variable x_{plc} equals 1 if product p is assigned to storage location l in class c, and 0 otherwise (Muppani & Adil, 2008). Key parameters include d_l, representing the distance of storage location l from input/output points, D_{pl}, denoting total picks required for product p from location l, and r, the unit handling cost per unit distance traveled. These parameters collectively characterize the warehouse system and enable quantitative performance assessment (Kovács, 2011).

The objective function minimizing total handling cost is formulated as:

$$\text{Minimize } HC = \sum_{c=1}^{C} \times \sum_{l=1}^{L} \times \sum_{p=1}^{P} \times 2rd_l D_{pl} x_{plc}$$

This formulation accounts for round-trip travel distances by incorporating the factor 2, representing travel from input/output points to storage locations and return. The model must satisfy several critical constraints ensuring feasible and operationally valid solutions (Muppani & Adil, 2008). First, each product must be assigned to exactly one storage location within one class:

$$\sum_{c=1}^{C} \times x_{plc} = 1 \forall l, p$$

Second, products with higher popularity values must be assigned to storage locations nearer to input/output points compared to products with lower popularity values within the same class. If product p has higher popularity than product p', and both are assigned to class c, then:

$$S_p \cdot x_{plc} \geq S_{p'} \cdot x_{p'l'c} \forall p, p', c, l, l' \text{ where } p \neq p', l < l', c = c'$$

This constraint ensures that higher-turnover items systematically occupy more favorable positions, aligning physical placement with access frequency patterns (Zhou et al., 2016).

Third, available storage capacity must accommodate assigned product volumes considering stacking heights and storage location characteristics. For each period t:

$$\sum_{p=1}^{P} \times \sum_{c=1}^{C} \times f_p \cdot I_p^t \cdot x_{plc} \leq h \cdot a_l \forall l$$

Where f_p represents the footprint density of product p, I_p^t denotes inventory quantity for product p during period t, h indicates storage level height, and a_l represents the footprint area of location l. These constraints ensure physically feasible storage assignments respecting volume limitations (Zhou et al., 2016). Additionally, the binary restriction on decision variables is imposed:

$$x_{plc} \in \{0,1\} \forall p, l, c$$

This mathematical model gives self-sufficient foundations to the computational solution techniques and analytical exploration of the ideal assignment forms (Muppani and Adil, 2008). The extensions of the models can include the further constraints representing the operational needs as product compatibility limitation, zoning of the hazardous materials or the temperature (Xiao and Zheng, 2010).

➢ *Integration of Closest Open Location Strategies Within Class-Based Framework*

The integration of closest open location principles into class-based storage structures develops better assignment policies which take advantage of both methods. Conventional policies based on classes will place incoming inventory randomly at class zones and may put items at different distances to optimal locations. Closest open location techniques are used to allocate systematically each arriving load into the closest possible storage location within the specified class area (Muppani and Adil, 2008). This strategic and tactic solution ensures the advantage of the strategic position of the turnover based on the classes and minimizes the travel distances of the separate assignments (Quintanilla et al., 2015). The improved policy involves a dynamic allocation decision based on the real-time availability of storage instead of the fixed allocation decisions that are made. More so, the integration recognizes that in-class distance heterogeneity can have a significant influence on aggregate performance and hence the calculation cost of distance-based selection is justified (Kovács, 2011).

Combined class-based closest open location policies implementation will need computational help of efficient identification of nearest available locations. Upon receiving the inventory to be stored, the warehouse management system is required to quickly find the assigned class zone where this product should be stored, determine the status of the storage areas under occupation, determine distances between the input point and all the existing locations, and select the one with the shortest distance. This sequence should run fast in order not to make delays in the material handling processes (Xiao & Zheng, 2010). The efficient data structure and search algorithms can be used to make the assignment decisions in real-time even within big warehouse facilities with thousands of storage points. Distance matrices are pre-computed to speed up the distance computation, whereas indexed occupancy databases enhance speedy availability queries (Derhami et al., 2020). Modern warehouse management systems that have sufficient processing power are sufficient to cope with the computational requirements. Also, the fallback procedures must be in place to make sure that there is continuity in the operation in case of unusual circumstances when the assigned class zones become full (Zhou et al., 2016).

It has been empirically proved that mixed-use class based closest open location policies provide better performance over their pure class-based or closest open location counterparts which act independently. The better policy focuses the high-turnover inventory in the favourable areas close to shipping locations and at the same time reduces the distance of the areas. Compared to either of the two distinct strategies of single strategy, this dual optimization is more successful in reducing the average travel distances (Muppani and Adil, 2008). Moreover, the combined policy dynamically follows the changing inventory structure and demand patterns, and properly manages the placement of storage as the turnover features are altered (Quintanilla et al., 2015). The implementation of research in a variety of warehouse settings confirms that there are consistent performance benefits, with an average of 15-35% in terms of travel distance savings over a baseline random assignment within classes. These enhancements are directly converted into cost savings in operations in terms of workforce and higher throughput capacity (Kovács, 2011). Besides, the policy requires fewer adjustments to be implemented by the current warehouse management systems and thus making it easier to adapt in the real-world settings (Xiao and Zheng, 2010).

C. Simulation-Based Optimization Approaches for Warehouse Design

- ***Rationale and Advantages of Simulation Modeling in Warehouse System Analysis***

The simulation modeling represents a most effective analytical system that can be used in comparing strategies of warehouse design, especially when there are stochastic behaviors of systems and dynamic interactions between them. The activities that are carried out in warehouses are characterized by many sources of uncertainty such as fluctuating demand trend, changes in production schedule, arbitrary equipment breakdowns, and uncertain processing time (Caron et al., 2000). These stochastic components introduce variability in the operations and this variability has a strong influence in the performance of the system although it is challenging to adequately represent these variations through pure analytical models (Le-Duc & de Koster, 2005). A discrete-event model is a straightforward model that explicitly models discrete operational events like inventory deliveries, order selections, and equipment movements, and behavior of a system state with time. Such a detailed model of representation allows a correct evaluation of performance in realistic operating conditions that includes various sources of randomness (Kachitvichyanukul and Sooksaksun, 2012). In addition, simulation models can be used to experiment with other policies and configurations with no inconvenience to real operations, which offer risk free evaluation environments (Caron et al., 2000).

To make mathematical problems tractable, analytical models often have assumptions simplified, which may not be accurate in application to complex real systems. Some of the common simplifications are that deterministic parameters, steady-state conditions, independent-operations, and simplified structure of the system are assumed (Le-Duc and de Koster, 2005). Although these assumptions permit the closed-form solutions and quick analysis, they can be inappropriate in describing the real-life behavior of a warehouse (Heragu et al., 2006). Simulation models can be used to support arbitrary level of complexity, reflecting detailed operational policies, equipment characteristics, spatial layouts, and resource constraints without the need to make restrictive assumptions. This allows larger fidelity system modeling, with better prediction of performance measures (Caron et al., 2000). Moreover, simulation offers an in-depth understanding of operations not just in terms of aggregate measure of performance, but also in terms of the bottlenecks, utilization, points of congestion and dynamic behavior informing improvement of designs (Kachitvichyanukul and Sooksaksun, 2012). The expressiveness of the modern simulation software also improves communication with the stakeholders and the model building on the design decision (Battini et al., 2016).

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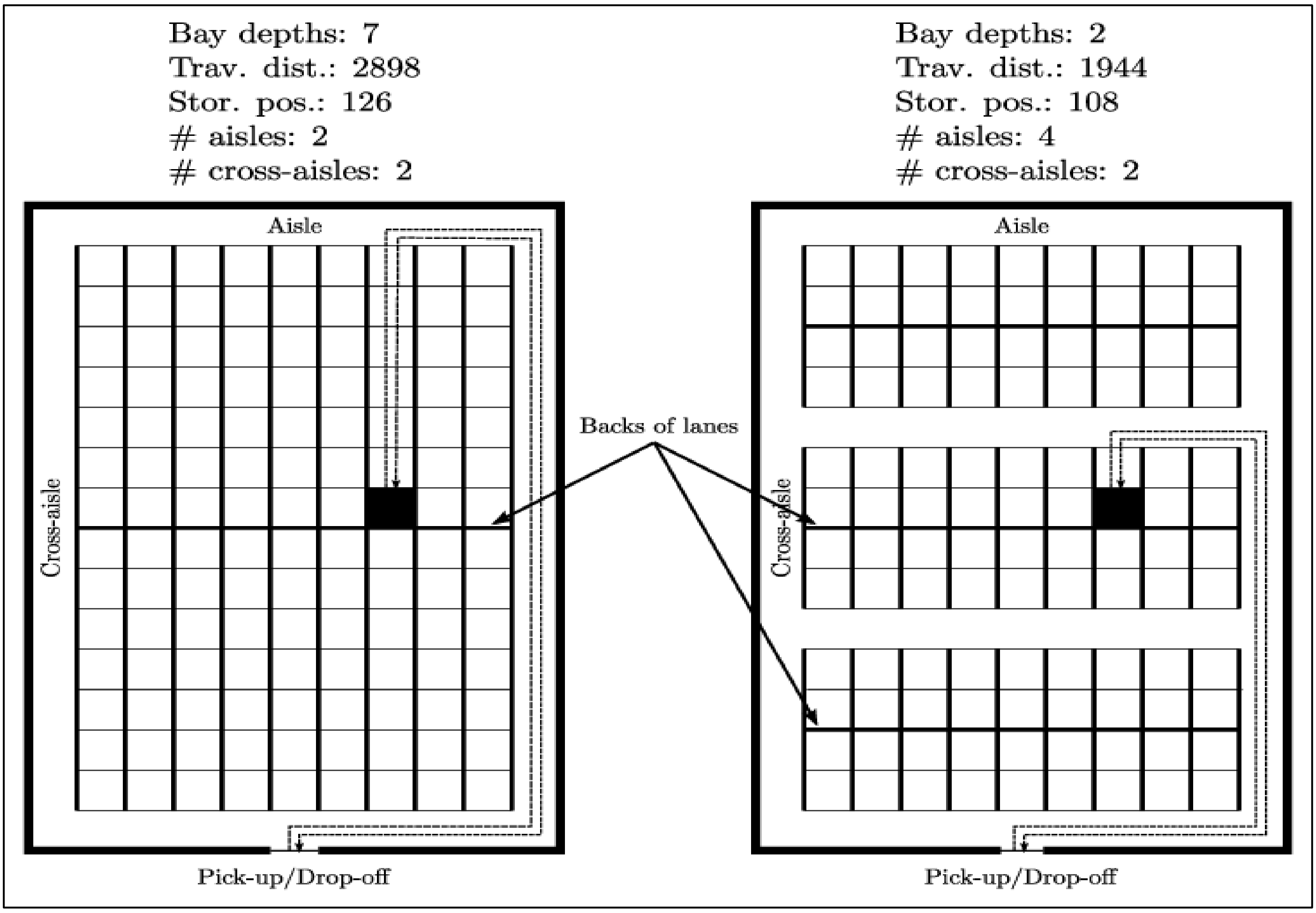

Fig 2 Space Utilization vs. Travel Distance with Respect to the Number of Aisles.

Combination of simulation and optimization algorithm develops potent methodologies in determination of optimal warehouse designs. Simulation is an advanced assessment capability, which evaluates candidate layout plans and policies of operation. Optimization algorithms search design spaces in a systematic way offering promising options to be simulated (Zhang and Li, 2024). This hybrid capitalizes on the advantages of the two-methods simulation representational accuracy and optimization search efficiency (Caron et al., 2000). Genetic algorithms and simulated annealing algorithm, particle swarm optimization and tabu search are examples of metaheuristic algorithms that have been implemented successfully with warehouse simulation models (Accomplished by 2008, p. 21). These are highly scalable algorithms that can search large discrete design spaces and find higher quality solutions without searching them exhaustively. Applications in research have shown that optimization based on simulation rediscovers designs of a warehouse that are significantly better than designs that are created manually and can offer 10-30% better operational performance metrics (Kachitvichyanukul, Sooksaksun, 2012). Additionally, the methodology allows a sensitivity analysis of the performance strength of different operational conditions, which is suitable to make risk-sensitive decisions (Chen et al., 2011).

Figure 2 shows the correlation between the distance travelled and the use of space in different number of bays in a warehouse plan. The graph shows the inherent trade off between the two performance dimensions, in which space utilization (measured in percent) will be presented on the left vertical axis and the total travel distance (measured in thousand miles) will be presented on the right vertical axis. Trends on space utilization show a tendency of general downward trend as the number of bays increases, between 2 and 20 with the first one being 48 to 40% and the second being 33 to about 29 thousand miles. This visualisation confirms that the objectives need to be optimized to ensure that the other objective is compromised and thus the use of multi-objective optimization methods in warehouse design is justified (Derhami et al., 2020).

- ➢ *Discrete-Event Simulation Model Architecture for Warehouse Operations*

The discrete-event simulation models are the representations of warehouse operations in the form of discrete events that happen at a particular point of simulated time. The events are associated with operational activities, e.g. inventory arrivals, storage assignment, order releases, picking operation, and shipment completion. The simulation has an event list that is arranged in chronological order, and processes each event one after another and the corresponding effect on system state is recorded (Caron et al., 2000). Event

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execution can plan the future events, which provides dynamic operational processes that change depending on system conditions and stochastic processes (Kachitvichyanukul & Sooksaksun, 2012). The event-based architecture is a natural model of the warehouses only that activities are performed by events, as opposed to time-based activities. Also, the discrete-event paradigm is computationally efficient because it supports the advancement of the simulation between the events over time instead of increasing continuously in time (Derhami et al., 2020).

The warehouse simulation model architecture has several basic components, which denote physical and operational system elements. Storage location entities can be described as physical places where inventory is housed, and they have characteristics such as coordinates, capacity attributes, occupancy status, as well as accessibility properties (Heragu et al., 2006). Inventory entities are personal units of products or unit loads, which trace the identities of items, their quantity, storage location, and time. The material handling equipment entities are the forklifts, automated guided vehicles or other movement devices, whose position coordinates, load status, and task assignments are kept (Derhami et al., 2020). The model monitors the movement of equipment in the facility and evaluates the time by using distances, speeds, and pathway networks (Chen et al., 2011). Order entities indicate picking needs, the products required, the quantities, the priorities, and the destination docks. All these forms of entities represent the key attributes of the warehouse operations without compromising the computational ease (Caron et al., 2000).

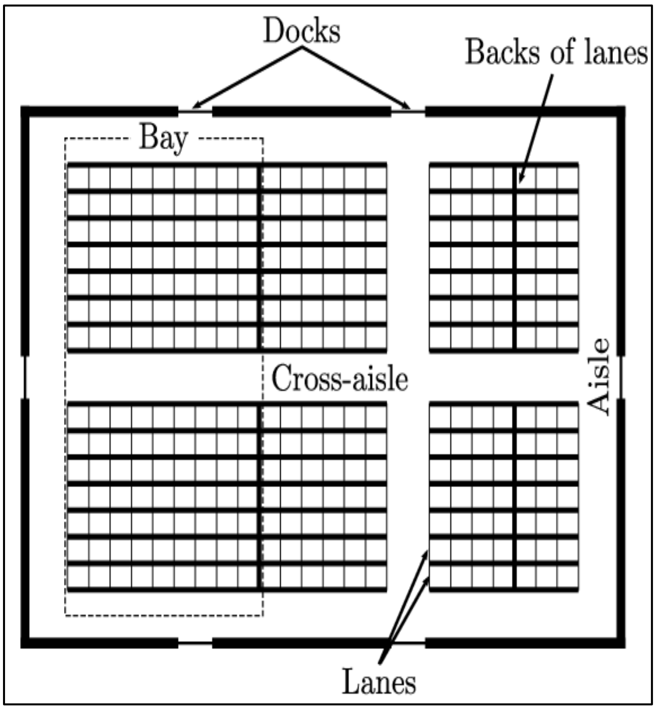

Fig 3 Components of a Conventional Block Stacking Layout.

Figure 3 shows the basic elements of a typical block stacking warehouse design, where the space layout of the major structural elements is shown. The diagram depicts the presence of docks at the facility perimeter, bays as the main storage structures, lanes running across aisles in each storage, cross-aisles giving perpendicular routes between the aisles, and the back of lanes reflecting the limit of the depth of storage location. This arrangement is the normal block stacking design, in which the inventory is stacked in lanes stretching out of major aisles, and it moves across the aisles in cross directions (Derhami et al., 2020). These elements are clearly defined and this offers the basis of the way layout design variables impact on storage capacity and travel distance requirements.

The type of events used in warehouse simulation models is also associated with the main activities of operations that should be updated in terms of state and decision logic. Production pick-up events are the entries of manufactured or received inventory that needs to be in storage. The event recognises material handling equipment available, gives out storage location based on the assigning policies, ships equipment to pick loads, and allocates the next delivery occasion depending on the computed travel-time (Derhami et al., 2020). Lane drop-off events involve the delivery of equipment to specific storage locations that puts the inventory positions and equipment status current. Storage operations are completed with replenishment events that enable storage capacity and release equipment to be used in the next task (Derhami et al., 2020). Order picking starts with outbound pick-up events, which identify the needed storage spots, dispatching equipment and organize retrieval events (Matusiak et al., 2014). Picking operations, inventory being removed out of storage, and loading equipment are done by retrieval events. The fulfillment of orders is accomplished using the Truck drop-off events, where the selected products will be transported to shipping stations, and equipment will be released. Parking vehicles involves returning idle equipment into special parking spots once they are finished with the parts of work that are assigned to them (Chen et al., 2011). Such an extended event taxonomy allows the representation of the patterns of material flow and equipment use in the work of a warehouse in details.

➢ *Stochastic Parameter Modelling and Variability Representation*

Proper simulation of the warehouses needs the right representation of stochastic operational parameters creating system variability. The production rates have time variations because of performance fluctuations of equipment used, maintenance processes, fluctuations of operator efficiency and limitations of raw materials. Simulation models describe the uncertainty in the rate of production in terms of probability distributions learned on historical data, or defined based on process knowledge (Derhami et al., 2020). Examples of such common distribution families are normal distributions of symmetric variation, lognormal distributions of positively-skewed processes, and empirical distributions of multimodal patterns of interest. The production rates in the simulation are drawn at random with given distributions during the scheduling of a manufacturing completion, producing realistic patterns of variability.

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Another important cause of operational uncertainty is demanding patterns which influence the performance of the warehouses. Orders of customers are received irregularly with time variable items in terms of product make-up and quantities. The Poisson processes or non-homogeneous Poisson processes are usually used to model order arrival processes based on their time-dependent characteristics that show the changes in arrival rates depending on the day of the week or seasons (Matusiak et al., 2014). Sampling of individual order characteristics such as product mix and quantities is done on relevant distributions based on historical order data. This stochastic demand model allows the simulation models to assess the performance of the warehouse when operating under realistic operation conditions because of demand uncertainty. Sensitivity analysis of the system response to various demand conditions offers information regarding the robustness of the system and the capacity sufficiency.

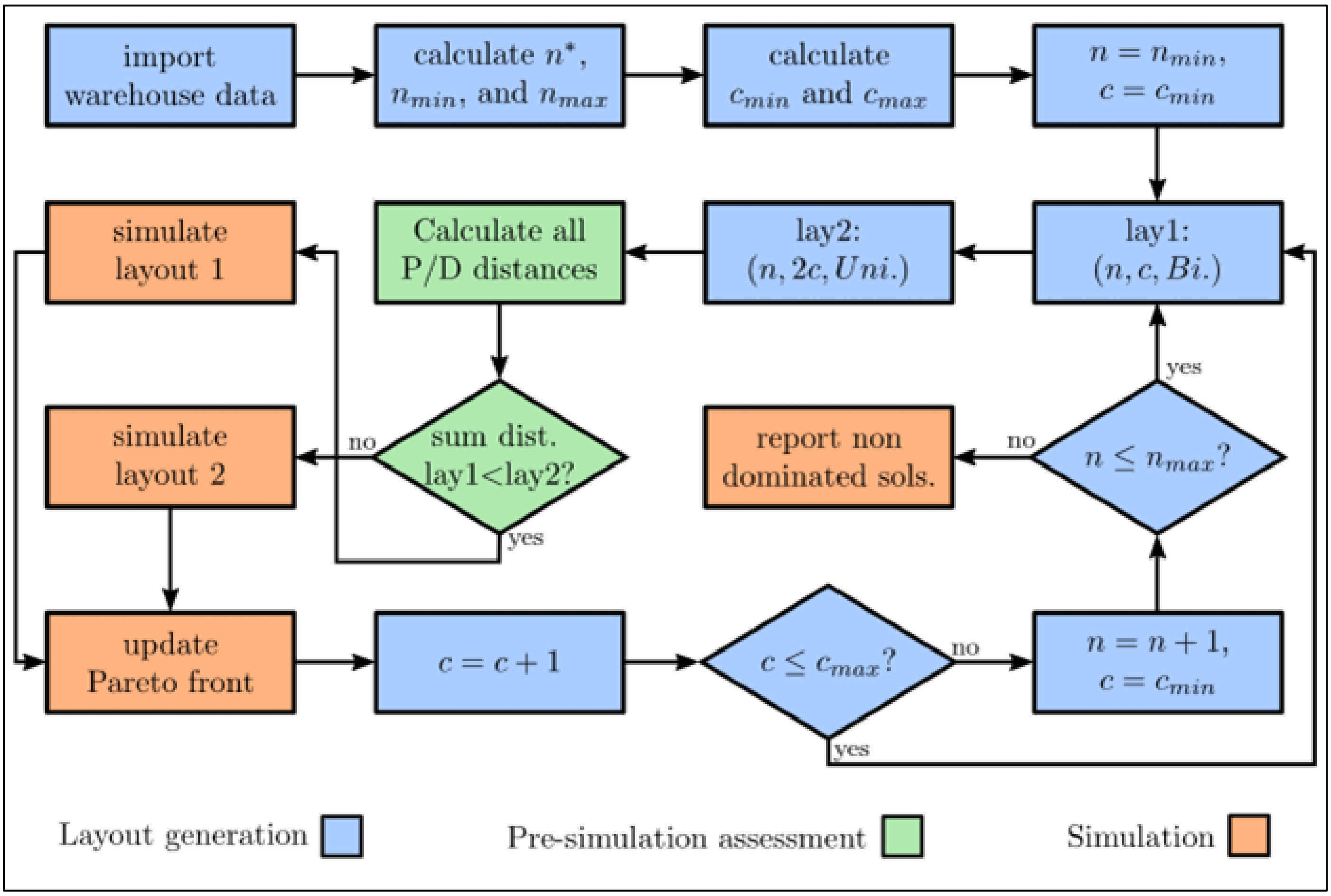

Fig 4 Flowchart of the Proposed Model

Figure 4 presents the comprehensive flowchart of the proposed warehouse layout optimization model, depicting the integrated methodology encompassing layout generation, pre-simulation assessment, and simulation-based evaluation stages. The flowchart begins with importing warehouse data and calculating fundamental parameters including optimal aisle count (n^*), minimum and maximum aisle bounds (a_{min}, a_{max}), and cross-aisle constraints (c_{min}, c_{max}). The methodology then produces layout scenarios in a systematic way, pre-simulates each layout by calculating distances to understand which solutions are dominated and simulates the non-dominated layouts in detail by using discrete-event simulation. This is repeated until every possible configuration within given constraints is explored, and eventually a Pareto front of optimal solutions that optimizes the use of space whilst satisfying the need of travel distance is obtained (Derhami et al., 2020). Three stage architecture layout generation (blue boxes), pre-simulation assessment (green boxes) and simulation (orange boxes) give a systemized process of efficiently exploring blocs of complex designs without compromising the quality of the solution.

There is variability in material handling operation times, which is caused by several factors such as distances, speed of equipment, performance of the operators, congestions, and complexity in task performing. Although the travel times are partly based on the deterministic distances between the points, the real time is different because of acceleration/deceleration points, avoidance of obstacles and variations in the speed. The simulation models denote the consideration of time variability through the introduction of stochastic in the distance-based travel time estimations (Battini et al., 2016). Realistic variations in performance are modelled by random variations in speeds and task-specific variations in speed. Set up, positioning and handling activities that are associated with variability are part of loading and

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unloading times. Full coverage of the uncertainties in operational times allows the simulation models to produce performance distributions instead of singleton estimations that can be used to make risk-taking decisions. The use of common random number streams between design choices ensures lower variation in the performance comparisons that enhance the statistical effectiveness of a simulation experiment.

➢ *Performance Metrics Collection and Statistical Analysis Methods*

Simulation models are used to produce detailed performance data that will allow a close assessment of the options in the design of the warehouse. Travel distance measures are determined by addition of distances covered by handling machinery in all operations activities in simulating processes. The comparison of loaded and unloaded travel distances allows separate tracking of these variables and understanding the pattern of equipment use and the possibility of movement consolidation (Derhami et al., 2020). Average travel distance per operation equalizes the total distances by volumes of activities making it easy to compare results in different scenarios with various throughput volumes. Distance distributions indicate variability and detect extreme cases that need to be taken care of.

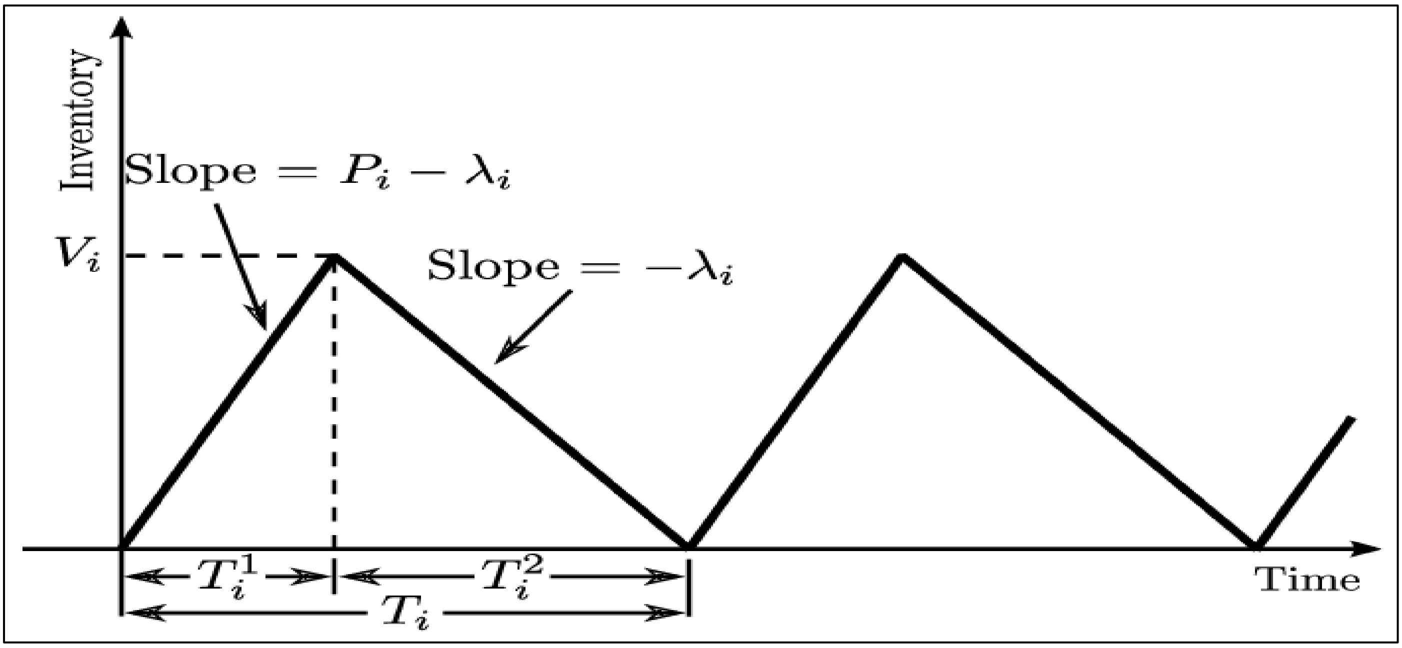

Fig 5 Changes in the Inventory of SKU i Over its Cycle Time, $P_i > \lambda_i$.*

Measures of storage space utilization determine the level of efficiency with which warehouse capacity is being used to store inventory. Instantaneous utilization is a measure of the fraction of capacity that is used at a given time, which changes over time with the same variation as inventory cycles. Aggregate metrics based on the dynamics of long-term simulation periods of time-averaged utilization are collected (Derhami et al., 2020). The productive storage and wasted capacity can be separated into the utilization, with the accessibility waste and the honeycombing waste singly differentiated. These specific measures both detect areas of improvement and measure trade-offs between capacity efficiency and operation performance. Also, the simulation records were the situations when the operations are constrained by storage capacity revealing sufficiency of available space under given demand conditions.

Figure 5 shows the inventory of one SKU in one operational cycle time whereby the inventory is shown to vary because of replenishing the production and depleting demand. The quantity of inventory is presented in the vertical axis and time is used in horizontal axis demonstrating time evolution through repeated replenishing periods. The sawtooth pattern shows inventory increasing sharply during production periods (with slope $P_i - \lambda_i$representing the net accumulation rate when production rate $P_i$exceeds demand rate λ_i), then declining during demand-only periods (with slope $-\lambda_i$). Peak inventory reaches $V_t$before declining, and the pattern repeats with periods T_i^1, T_i^2, and total cycle time T_i. This inventory behavior directly influences honeycombing waste calculations, as lanes dedicated to specific SKUs contain varying occupancy levels throughout cycles (Derhami et al., 2020). Understanding these temporal dynamics enables more accurate waste estimation and supports optimization of storage assignment policies.

Material handling resource effectiveness is measured by equipment utilization and productivity measures. Equipment utilization is a calculation of timeframes; it is the percentage of the time that material handling equipment performs tasks as compared to periods when devices are not in action. High utilization shows that the resources are deployed efficiently, however, it can be an indication of the lack of capacity in case of delays in orders. Operational throughput is measured by using task completion rates in terms of orders received or inventory movement transactions carried out within a unit time (Chen et al., 2011). Labor productivity measures gauge the effectiveness of workers in picker-to-product designation

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where human operators carry out the order selection. Analysis of data generated by simulations should be done statistically using the right methods taking into consideration autocorrelation and run length determination and initial conditions. The periods of warming up eliminate transient effects of initializing and the result gives a steady-state performance measurement. Repeated independent replications by different random number streams allow confidence interval construction which quantifies the precision of the estimates. The methods of variance reduction such as common random numbers enhance comparison performance between design alternatives.

D. Problem Statement and Research Motivation

The modern practice in warehouse design has been experiencing tremendous challenges on how to ensure that the storage space utilization is high, and at the same time the material handling travel distance remains low. Such goals are in inherent conflict, and complex trade-offs are involved with systematic optimization methods that need to be optimized (Derhami et al., 2020). The conventional design processes based on simplified analytical models or heuristics are known to lead to poor designs that adversely affect the efficiency of operations and create too many costs. The literature available contains some significant gaps with respect to a limited practical applicability (Van Gils et al., 2018). Majority of the research has only been interested in space utilization optimization, without the implication of travel distance associated with design choices. On the other side, the research focusing on the minimization of travel distance focuses on it without sufficient consideration of the storage space and use effectiveness (Le-Duc & de Koster, 2005). There are few combined strategies that offer a simultaneous balance between both goals and consider the operational realities. This division on research emphasis causes problem to practitioners who want a detailed design advice (Heragu et al., 2006).

Moreover, the available models of warehouse design normally make simplified assumptions, which may not be true in real life application. Some of the common simplifications are constrained deterministic parameters, one-level storage structure, homogeneous product features and simplified operational policies (Heragu et al., 2006). In the real world, warehouses are characterized by stochastic demand and production, different levels of storage in each location, different product portfolio with different turnover profiles, and complex assignment policies with multiple objectives (Muppani and Adil, 2008). The difference between simplified analytical models and what is happening during operational complexity restricts the usefulness of the current research contributions. Also, most of the past research looks at individual elements of designs and not at the optimization of systems (Derhami et al., 2020). The configuration of the aisles, where to place cross-aisle, where to place storage location and class formation are interrelated issues that are not solved in a holistic manner but in a sequential fashion. Such a way of decomposition can overlook key synergies or trade-offs that can arise because of simultaneous optimization (Kachitvichyanukul and Sooksaksun, 2012).

In particular, the research will fill in the most important gaps by creating a combined simulation-based optimization model that will help optimize the design of warehouse layouts and the allocation of storage locations simultaneously. The method explicitly considers the various levels of storage per place, which allows depicting the use of vertical space realistically (Viveros et al., 2021). It includes stochastic operational parameters such as variable production rates, demand patterns and handling times which produce powerful designs that have good performance in uncertainty (Caron et al., 2000). The methodology identifies the best numbers of aisles and cross-aisles, cross-aisle formations, bay depth formations, cross-aisle types, storage classes formations and assignment policy of locations by multi-objective optimization. The holistic methodology is superior to the constraints of partial optimization techniques since it finds better overall solutions that effectively trade off competing goals (Derhami et al., 2020). Furthermore, the framework gives effective decision support tools that allow the practitioners to make trade-offs and to choose the proper designs with reference to the organization-specific cost structures and operational priorities.

E. Research Objectives

The primary objectives guiding this research investigation are:

- Develop a comprehensive simulation-based optimization framework integrating warehouse layout design with storage location assignment policy determination, enabling simultaneous optimization of spatial configuration and operational policies.
- Formulate mathematical models characterizing relationships between design variables and performance objectives, including closed-form solutions for optimal aisle numbers under common bay depth policies.
- Create discrete-event simulation models accurately representing warehouse operations including stochastic production processes, random demand patterns, material handling activities, and multi-level storage configurations.
- Implement metaheuristic optimization algorithms efficiently exploring design spaces to identify Pareto-optimal layout configurations balancing space utilization against travel distance minimization.

F. Research Contributions

This research advances warehouse design methodology and contributes to logistics systems engineering knowledge through several significant innovations:

- Development of integrated optimization framework: The research presents a novel simulation-based optimization approach simultaneously addressing layout design and storage assignment decisions previously treated independently, enabling discovery of superior coordinated solutions.
- Analytical model for optimal aisle configuration: A closed-form mathematical solution determining optimal aisle numbers maximizing space utilization under

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common bay depth constraints provides practical design guidance and accelerates computational optimization.

- Enhanced class-based storage policy: Integration of closest open location assignment within class-based frameworks creates an improved policy capturing benefits of both strategic class positioning and tactical distance minimization.
- Multi-level storage representation: Explicit modeling of vertical storage levels enables realistic assessment of cubic space utilization, distinguishing this work from prior research considering only floor-level storage positions.
- Comprehensive performance evaluation: Simultaneous quantification of space utilization efficiency, travel distance requirements, and operational costs through detailed simulation provides multidimensional design assessment supporting informed decision-making.

II. MATERIALS AND METHODS

A. Overall Research Framework and Methodological Approach

➤ *Integrated Optimization Framework Architecture and Component Relationships*

The methodology used in the research is based on a three-stage integrated optimization model that incorporates analytical modelling, discrete-event simulation, and metaheuristic search algorithms. The multi-dimensional warehouse design issue is systematically tackled using the framework of coordinated layout configuration analysis and operational policy analysis. The first phase produces candidate layout designs based on the systematic variation of important design parameters such as the aisle numbers, number of cross-aisles, bay depths, and directionality in cross-aisle. This guided generation scheme searches the design space in a thorough manner and uses analytical bounds based on mathematical models to restrict the number of computations (Derhami et al., 2020).

Pre-simulation assessment stage involves initial filtering of layout generated options, with dominated configurations being filtered out and then undergoes intensive simulation analysis. The calculation of rectilinear travel distances between all possible origin-destination pairs is done with reference to aisle networks and cross-aisle configurations of the layouts. The layouts that have a worse total travel distance than other layouts with the same space allocation are removed as non-competitive solutions (Derhami et al., 2020). This screening makes the computational load much less by eliminating clearly suboptimal configurations to further analysis. Pre-computed distance matrices are also stored to retained layouts, which hastens the processing of events when the simulation is underway. The analysis makes a distinction between unidirectional and bidirectional cross-aisle designs, choosing better directional ones where the layouts vary by this characteristic only, but the number of aisles and cross-aisles is the same.

The last step of simulation is a test of performance of filtered layout configurations in realistic stochastic operational conditions. All the candidate layouts are subjected to massive replication of simulation which gives statistical estimates concerning the efficiency of space utilization and material movement distance demands. The simulation model is the elaborated warehouse processes in terms of inventory deliveries as per the production schedules, storage location assignments as per the policies applied, material handling equipment operations, and order fulfillments (Caron et al., 2000). Realistic variability in operations is achieved because of the stochastic factors such as fluctuating rates of production, fluctuating demand patterns, and random handling times. Confidence interval Construction of confidence intervals based on multiple independent simulation replications with varying random number streams provides a measure of estimate precision. The performance outputs of all layouts considered produce Pareto frontier identification to display non-dominated solutions of the trade-off configurations of the competing space utilization and travel distance goals.

➤ *Mathematical Notation and Parameter Definition Framework*

Comprehensive mathematical notation enables precise model specification and unambiguous communication of analytical relationships. Index sets include $c$and c'representing storage classes where $c, c' \in \{1,2,\dots,C\}$, $l$and l'denoting storage locations with $l, l' \in \{1,2,\dots,L\}$, $p$and p'indicating products where $p, p' \in \{1,2,\dots,P\}$, and $t$representing time periods with $t \in \{1,2,\dots,T\}$. These indices facilitate compact mathematical expressions describing relationships among system entities.

Key dimensional parameters characterize physical warehouse attributes and operational requirements. Warehouse dimensions include length $S_l$measured in pallet positions, width $S_w$in pallet positions, and clear height $S_h$in distance units such as meters or feet. Aisle characteristics encompass width Aexpressed in pallet positions and total number $n_a$representing count of primary storage aisles. Cross-aisle attributes include width Cin pallet positions, total number n_c, and constraints on lane separation distances including minimum $L_{min}$and maximum L_{max}lanes between consecutive cross-aisles (Derhami et al., 2020). Product-specific parameters capture inventory characteristics including production batch quantity Q_i, production rate $P_i$in pallets per time unit, demand rate $\lambda_i$in pallets per time unit, pallet height $H_i$in distance units, and stackable height $Z_i$representing maximum safe stacking levels.

Decision variables represent controllable choices determining warehouse configuration and operational policies. The binary variable $x_{plc} \in \{0,1\}$indicates whether product $p$is assigned to storage location $l$within class c, with $x_{plc} = 1$signifying assignment and $x_{plc} = 0$indicating non-assignment. Bay depth $\bar{x}$measured in pallet positions determines the number of pallet positions extending from aisles into storage bays, directly affecting both space utilization and accessibility. The optimal number of aisles

n_a^*represents the analytically-derived configuration maximizing space efficiency under specified constraints. Performance metrics include wasted storage volume percentage W, total required vehicle count N_v, loaded travel distance D_u, unloaded travel distance D_l, and simulation duration parameters including total simulation time $T^s$and warm-up period T^w(Derhami et al., 2020).

➤ *Computational Implementation Platform and Algorithm Development Environment*

The entire implementation of the optimization framework will use Python 2.7 programming language which was chosen due to its massive scientific computing library, flexible object-oriented design, and more established discrete-event simulation packages. SimPy discrete-event simulation library offers underlying event scheduling, process administration, and resource distribution features based on warehouse operation modelling. NumPy and SciPy libraries provide high performance numerical algorithms such as matrix operations, statistical distributions, and optimization algorithms. Pandas' data frames are used to manage data structure and warehouse configuration parameter, product characteristics, and simulation output results (Zhang and Li, 2024). Pareto frontier, performance distribution, and layout configuration graphs are created using Matplotlib visualization libraries to aid reading of the results.

Computational experiments are run on high-performance computer cluster systems using Intel Xeon E5-2660 processors with a clock speed of 2.6 GHz and 128 GB RAM on a node. Multiprocessing libraries are used to utilize parallel processing capabilities of multiprocessing libraries, which allocate independent simulation replications to ten processor cores at the same time. Such parallelization has a significant effect on the overall computation time, as many layout options can be calculated in realistic time scales. All simulation scenarios run in separate processor cores and do not share a resource which would cause them to contend and can ensure a reproducible outcome. Load balancing algorithms ensure there is balanced distribution of computational workload to processors available so that the resource utilization efficiency is optimised (Derhami et al., 2020).

Execution protocols in simulation are based on best practices that provide statistical validity and reliability of the results. One month warm-up periods approximate time, which wipes out transient startup biases and enable systems to stabilize to a steady-state operating point before the performance measurement commences. The overall time taken in the simulation will be eight months, which will allow it to observe it enough to estimate long-term performance. There are several independent replications with alternate random number seeds that produce statistical samples that allow the construction of confidence intervals. The random number streams are common to layout options and employ variance reduction methods that enhance the accuracy of the comparison through removal of unnecessary sources of random variation (Caron et al., 2000). Output analysis uses the well-established statistical analysis tools of autocorrelation in time-series simulation data.

B. Analytical Models for Optimal Aisle Configuration Determination

➤ *Space Utilization Model Formulation and Waste Component Decomposition*

The use of space is the basic parameter of warehouse capacity and operational economics, which is the ratio between the available volume that is successfully utilized to store inventory. The model that is used to quantify space utilization breaks down the total wasted volume into the components that represent various physical and functioning phenomena. Based on Derhami et al. (2020), the mean wasted storage volume on block stacking warehouse designs is defined as:

$$\bar{W} = AS_hS_wn_a + \frac{S_h}{2}\sum_{i\in I} \times x_i + \sum_{i\in I} \times \frac{1}{2P_iZ_i}[(Q_i(S_h - Z_iH_i) - Z_iH_i)(P_i - \lambda_i) - \lambda_i(2S_h - Z_iH_i)]$$

This formulation partitions waste into three distinct components with different operational origins. The first term $AS_hS_wn_a$represents accessibility waste attributable to aisle space requirements. Aisles of width Apallets extend the full warehouse width $S_w$and height S_h, consuming volume proportional to aisle count n_a. This space enables material handling equipment access but cannot accommodate inventory storage, constituting unavoidable waste necessary for operational functionality (Le-Duc & de Koster, 2005).

The second term $\frac{S_h}{2}\sum_{i\in I} \quad x_i$captures additional accessibility waste associated with lane depths, where $x_i$represents the assigned depth for product i. Shallower lanes dedicate proportionally more volume to accessibility relative to storage capacity compared to deeper lanes. This component reflects the geometric relationship between lane dimensions and accessible storage positions. The third term quantifies honeycombing waste generated when lanes become partially occupied. Honeycombing occurs because block stacking systems temporarily dedicate lanes to specific products during replenishment and depletion cycles, preventing other products from utilizing vacant positions within partially-occupied lanes (Derhami et al., 2020). The magnitude depends on production batch quantities Q_i, production rates P_i, demand rates λ_i, pallet heights H_i, and stacking limits Z_i.

➤ *Optimization Model Development for Common Bay Depth Configuration*

The optimization problem determining the optimal number of aisles under common bay depth constraints seeks to minimize total wasted volume while satisfying dimensional and operational requirements. Common bay depth policies mandate that all storage bays maintain identical depths, simplifying operational management and eliminating complex lane assignment decisions. Under this constraint, the relationship $\sum_{i \in I} x_i = N_s \bar{x}$ holds, where N_s represents the total number of SKUs and $\bar{x}$ denotes the common bay depth applied uniformly. Substituting this relationship into the waste expression and removing constant terms irrelevant to optimization yields the simplified objective function:

$$\text{Minimize } AS_h S_w n_a + \frac{1}{2} S_h N_s \bar{x}$$

This objective must satisfy the fundamental dimensional constraint ensuring that bay depths and aisle widths collectively span the warehouse length. Assuming bays are arranged back-to-back with shared aisles between opposing bay faces, the constraint becomes:

$$2n_a \bar{x} + n_a A = S_l$$

This relationship specifies that n_a aisles create $2n_a$ bay faces, each with depth $\bar{x}$, plus aisle width A for each of the n_a aisles, summing to total warehouse length S_l (Derhami et al., 2020). Solving this constraint for $\bar{x}$ yields:

$$\bar{x} = \frac{S_l - n_a A}{2n_a}$$

Substituting this expression into the objective function eliminates $\bar{x}$ as an independent variable, producing an unconstrained single-variable optimization problem in n_a:

$$\text{Minimize } AS_h S_w n_a + \frac{S_h N_s}{4n_a}(S_l - n_a A)$$

This objective simplifies to:

$$\text{Minimize } AS_h S_w n_a + \frac{S_h N_s S_l}{4n_a} - \frac{S_h N_s A}{4}$$

The constant term $-\frac{S_h N_s A}{4}$ does not affect the optimization and can be removed, yielding:

$$\text{Minimize } f(n_a) = AS_h S_w n_a + \frac{S_h N_s S_l}{4n_a}$$

➢ *Analytical Solution Derivation and Optimality Conditions*

The optimal aisle number n_a^* minimizing the objective function is determined through calculus-based optimization. Taking the derivative of $f(n_a)$ with respect to n_a produces:

$$\frac{df}{dn_a} = AS_h S_w - \frac{S_h N_s S_l}{4n_a^2}$$

Setting this derivative equal to zero identifies critical points:

$$AS_h S_w - \frac{S_h N_s S_l}{4n_a^2} = 0$$

Solving for n_a yields:

$$n_a^2 = \frac{S_h N_s S_l}{4AS_h S_w} = \frac{N_s S_l}{4AS_w}$$

Taking the positive square root produces the closed-form solution:

$$n_a^* = \sqrt{\frac{S_l N_s}{4S_w A}}$$

This analytical result provides immediate computation of optimal aisle numbers given warehouse dimensions, SKU count, and aisle width specifications. The second derivative confirms this critical point represents a global minimum. Computing $\frac{d^2 f}{dn_a^2}$ yields:

$$\frac{d^2 f}{dn_a^2} = \frac{S_h N_s S_l}{2n_a^3}$$

Since all parameters S_h, N_s, S_l, and n_a are positive, this second derivative remains positive for all feasible n_a values, confirming that $f(n_a)$ is a convex function with a global minimum at n_a^* (Derhami et al., 2020). The unimodal nature guarantees no local minima exist, ensuring the analytical solution represents the globally optimal configuration.

➢ *Integer Solution Treatment and Practical Implementation*

The analytical solution n_a^* typically produces non-integer values, while physical implementations require integer aisle counts. The optimal integer solution is determined by evaluating the objective function at the two nearest integers, $\lfloor n_a^* \rfloor$ and $\lceil n_a^* \rceil$, selecting the value yielding lower waste. For $n_a^* = 5.7$, both $n_a = 5$ and $n_a = 6$ are evaluated, choosing the superior alternative. Once the optimal integer aisle count is established, the corresponding optimal common bay depth follows from:

$$\bar{x}^* = \frac{S_l - n_a^* A}{2n_a^*}$$

If $\bar{x}^*$ is non-integer, practical implementation creates $2n_a^*$ bays with depth $\lfloor \bar{x}^* \rfloor$ pallets, then distributes the remaining $S_l - n_a^*(2\lfloor \bar{x}^* \rfloor + A)$ pallet positions equally among all bays. This approach ensures complete space utilization while maintaining nearly uniform bay depths (Derhami et al., 2020). The analytical model provides valuable practical guidance and establishes bounds for computational optimization search spaces, substantially reducing the number of layout configurations requiring simulation evaluation.

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C. Layout Scenario Generation and Design Space Exploration

➢ *Aisle Number Bounds Determination Through Analytical and Empirical Methods*

The detailed study of the design space of warehouse layouts needs the systematic creation of the candidate configuration within the practicable range of the main design factors. Aisles level is also one of the main design parameters that inherently influence the use of space and travel distances, which requires a serious choice of exploration limits. Lower bound a mined upper bound a max determine the range of aisle numbers considered, which have a direct impact on the requirements of computers and the quality of solutions. Too restrictive constraints may remove the most efficient set of parameters whereas too relaxed set constraints may create prohibitive computational costs (Derhami et al., 2020).

The analytical model developed previously provides theoretical guidance for establishing aisle number bounds. The optimal aisle count n_a^*derived through waste minimization serves as a natural anchor point for defining exploration ranges. Initial experimental investigations across diverse problem sizes examined layouts with aisle numbers ranging from $a_{min} = \alpha n_a^*$to $a_{max} = \beta n_a^*$, where $\alpha$and βrepresent scaling factors. Preliminary experiments employed $\alpha = 0.8$and $\beta = 1.5$, generating wide ranges ensuring no potentially optimal solutions were inadvertently excluded. Analysis of resulting Pareto frontier solutions across test problems spanning 10 to 300 SKUs revealed consistent patterns (Derhami et al., 2020). No optimal solutions contained fewer than n_a^*aisles, indicating that reducing aisle numbers below this threshold deteriorates both space utilization and travel distance objectives simultaneously.

Based on these empirical observations, the refined lower bound is established as $a_{min} = n_a^*$, eliminating unnecessary evaluation of suboptimal configurations with insufficient aisles. The upper bound determination recognizes that travel distance improvements diminish as aisle numbers increase beyond certain levels while space utilization deteriorates monotonically. Empirical analysis demonstrated that solutions with aisle counts exceeding $1.4n_a^*$rarely appeared in Pareto frontiers, suggesting limited value from additional aisles beyond this point. Consequently, the upper bound is set as $a_{max} = 1.4n_a^*$, balancing comprehensive exploration against computational efficiency (Derhami et al., 2020). These refined bounds substantially reduce the number of layout scenarios requiring evaluation while preserving all potentially optimal configurations, achieving an effective compromise between solution quality and computational tractability.

➢ *Cross-Aisle Number Bounds and Configuration Alternatives*

Cross-aisles are the straight lines that cut the major storage aisles in form of short cuts, which minimizes the travel distances, especially where a warehouse has a huge storage space. Another vital design variable that needs to be experimented on systematically is the number of cross-aisles creep. In contrast to aisle numbers, analytical models that forecast the optimum number of cross aisles are inefficient because of complicated interactions among aisle networks, cross-aisle locations, and random travel distributions. Therefore, practical constraints, along with the use of empirically determined approaches set the boundaries of the number of cross aisles (Pohl et al., 2009).

The minimum number of cross-aisles is typically set to $c_{min} = 2$, ensuring at least one cross-aisle exists near each short side of the warehouse to facilitate equipment access to storage areas from input/output points. The maximum number is determined by specifying minimum allowable distances between consecutive cross-aisles, expressed as minimum lane counts L_{min}isolating neighbouring cross-aisles. This limitation helps to avoid too much cross-aisle density that will break up storage spaces in an ineffective manner. The maximum number of aisles across the minimum separation limit is:

$$c_{max} = \lfloor \frac{S_w + L_{min}}{L_{min} + 2C} \rfloor$$

Where Crepresents unidirectional cross-aisle width in pallet positions. Empirical analysis suggested $L_{min} = 0.1S_w$ establishes a reasonable separation, not too fragmented but with enough cross aisles to minimize the number of travel miles (Derhami et al., 2020). This formulation produces the upper bounds that cover all the cross-aisle configurations of Pareto-optimal solutions of various test problems.

Cross-aisle directionality is also another design factor that influences space use and operational capacity. Unidirectional cross-aisles allow equipment to travel in one direction with a requirement of half the width of the bidirectional versions but it may limit the routing capabilities. Two-way traffic is made in two-way cross-aisles, which occupy space, although they offer increased flexibility of operation (Derhami et al., 2020). The layout generation process generates the configuration of a pair of scenarios in each combination of aisles and cross-aisles: one configuration with bidirectional cross-aisles and the other with twice as many unidirectional cross-aisles in opposing direction pairs. This pairing allows one to make a fair comparison between directionality options but retain the same amount of space allocated to cross-aisle functions. The pre-simulation assessment phase then filters out dominated alternatives and only the superior configurations are left to be critically evaluated in terms of simulation.

➢ *Layout Scenario Enumeration and Generation Procedures*

The complete layout scenario generation process systematically enumerates combinations of design variable values within established bounds, creating a comprehensive set of candidate configurations for evaluation. Given bounds $a_{min} \leq n_a \leq a_{max}$for aisle numbers and $c_{min} \leq n_c \leq c_{max}$for cross-aisle counts, plus binary directionality choices for cross-aisles, the total number of generated scenarios is $(a_{max} - a_{min} + 1)(c_{max} - c_{min} + 1) \times 2$. This enumeration ensures systematic coverage of the bounded design space without inadvertently overlooking potentially optimal configurations (Derhami et al., 2020).

For each combination of aisle count $n_a$and cross-aisle count n_c, bay depth follows deterministically from the dimensional constraint $\bar{x} = \frac{S_l - n_a A}{2n_a}$, maintaining consistency with the common bay depth policy. Cross-aisles are placed evenly on the length of the warehouse, with a consistent space between the two successive cross-aisles. For $n_c$cross-aisles spanning warehouse width $S_w$containing $N_l$total lanes, the spacing interval is approximately $\frac{N_l}{n_c+1}$lanes. This uniform spacing distributes cross-aisle benefits evenly throughout the storage area, avoiding concentration of shortcuts in particular zones while other areas suffer from limited accessibility (Pohl et al., 2009).

The generation algorithm implements systematic enumeration through nested iteration loops. The outer loop traverse's aisle numbers from $a_{min}$to a_{max}, computing corresponding bay depths for each aisle count. The inner loop iterates through cross-aisle numbers from $c_{min}$to c_{max} for each fixed aisle count. Under the innermost scope, bidirectional and unidirectional cross-aisle arrangements are produced in each pair of aisle-cross-aisle. Every scenario that had been generated is described by a data structure that logs the entire configuration specification in terms of aisle count, cross-aisle count, bay depth, cross-aisle type, and calculated layout dimensions. Such formal expression promotes further processing procedures such as pre-simulation analysis and simulation implementation (Kachitvichyanukul and Sooksaksun, 2012).

D. Pre-Simulation Assessment and Distance Matrix Computation

➢ *Travel Distance Calculation Methods for Rectilinear Warehouse Networks*

The correct evaluation of the material handling travel distances involves the determination of shortest paths through warehouse aisle and cross-aisle networks between all possible origin-destination location points. Block stacking warehouses have a usual rectilinear pattern of travel where all equipment moves in orthogonal aisles and cross-aisles instead of diagonal or arbitrary routes. The closest line distance between two points $(x_o, y_o)$and (x_d, y_d)following aisle networks is determined by identifying the minimum-length path traversing permitted pathways (Roodbergen & Vis, 2009).

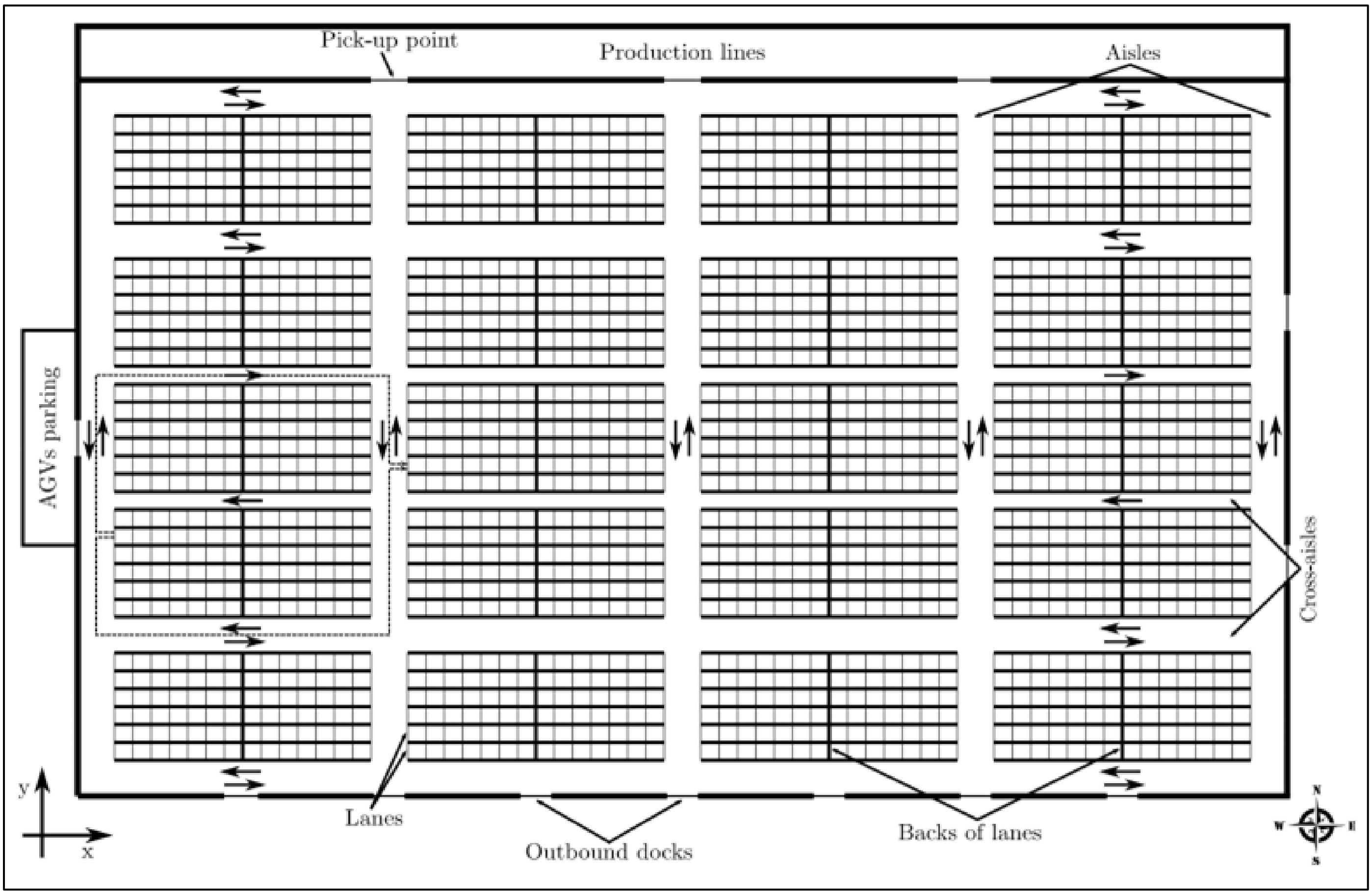

Fig 6 Components of the Layout and their Relative Configurations.

The travel distances between locations of stores will take a route made up of movements along at most two aisles (containing the origin and destination points) and one cross-aisle along which the aisles interconnect. There are several different paths that can find the same minimum distance, yet one of them is kept to ensure efficiency during calculations (Derhami et al., 2020).

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Figure 6 depicts the overall layout design that reveals the spatial associations of all the significant components of the warehouse. The diagram is used to indicate the pickup point, which is located at the facility perimeter, production lines that are carried along one side, several aisles that are oriented in different directions where they are used to provide the primary access pathways, lanes that run perpendicular to the aisles and form the main storage structure, backs of lanes that indicate the boundaries of the storage depth and cross-aisles (VGA-aisles) that cut across the primary aisles to provide perpendicular routing options (Derhami et al., 2020). The compass-oriented system of coordinates (N-S-E-W) sets directional standards of calculations of the distance and routing logic. This layout illustrates the interaction between layout elements in establishing the properties of storage capacity and travel distance with relative arrangement of pickup points, aisles, and cross-aisles being the basic determinants of operational efficiency.

To move west to east between storage locations, the shortest route can either be along the nearest available cross-aisle northward of the source of the movement or the nearest available cross-aisle southward of the source of the movement. The distance to the north route is as follows:

$$D_W^{N\to E} = \begin{cases} |\, y_c - y_o \,| + |\, y_c - y_d \,| + |\, x_d - x_o \,| & \text{if } y_c \neq \emptyset \\ \infty \end{cases}$$

Where $y_c$represents the y-coordinate of the nearest northward cross-aisle permitting eastward travel. If no eligible northward cross-aisle exists, the distance is set to infinity, effectively excluding this path from consideration. Similarly, the southward path distance $D_W^{S\to E}$is computed using the nearest southward cross-aisle coordinates. The minimum distance for westward-to-eastward travel is then:

$$D_{W\to E} = \min\{D_W^{N\to E}, D_W^{S\to E}\}$$

Opposite direction travel distances $D_{E\to W}$are computed analogously but may differ from $D_{W\to E}$when unidirectional cross-aisles impose asymmetric routing constraints (Derhami et al., 2020). North-south movements along aisles follow simpler distance calculations since aisles are inherently bidirectional to accommodate lane access operations. These distances are computed as Manhattan distances:

$$D_{N\leftrightarrow S} = |\, y_o - y_d \,| + |\, x_o - x_d \,|.$$

- *Comprehensive Distance Matrix Construction and Storage Structures*

The pre-simulation evaluation phase builds up all-to-all origin-destination distance matrices of the shortest path distances in each of the layout configurations generated. These matrices include dispersion between storage points, dispersion between storage points and production pick-up, dispersion between storage points and shipping docks and the combination of all production areas, docks, and vehicle parking spots. The full distance data allow quick distance lookups when processing simulation events without having to repeat shortest path computation, which would otherwise place a heavy computational burden (Caron et al., 2000).

Distance matrices are then done by a method of two-dimensional array data structure using identifiers of location of origin and destination. In layouts involving Storage locations, the storage-storage distance matrix is dimensional $L \times L$, with element (i,j)storing the shortest distance from storage location $i$to storage location j. Separate matrices capture distances from storage locations to Mproduction pick-up points (dimension $L \times M$), from pick-up points to storage locations ($M \times L$), and the same applies to shipping docks and parking areas. Efficient matrix storage takes advantage of possible asymmetries in the case of bidirectional travel and keeps different records in the origin-destination pairs with asymmetric distance related to the unidirectional cross-aisle constraints (Zhang and Li, 2024).

The storage needs of pre-computation of full distance matrices are modest but have significant computational advantages when running a simulation. Suppose a simulating process of 100,000 material handling processes within a time span. Assuming every operation involves the calculation of the distances including the shortest path search in an aisle network comprising 50 storage locations and 5 cross-aisles, the cumulative effort in terms of computations is high. Pre-calculated matrices optimize the distance query to an array look-over operation that needs minimum processing time. The memory to hold distance matrices is manageable even with large warehouses; a warehouse that has 1,000 storage and 20 pick-up/drop-off points needs memory of the order of $(1000^2 + 1000 \times 20 \times 2) = 1{,}040{,}000$ distance values, easily accommodated in modern computing systems (Derhami et al., 2020).

- *Preliminary Layout Screening and Dominated Solution Elimination*

Pre-simulation assessment is preliminary screening of the layout before it is subjected to computationally expensive simulation analysis to reject the obviously dominated layout configurations. A dominance evaluation can be made directly between two layouts whose absolute volumes assigned to cross-aisles is the same and only the characteristics of the cross-aisle directionality can differ. Each layout is a layout of n_cbidirectional cross-aisles using a cross-aisle width of 2Cpallets, and a total cross-aisle volume. $n_c \times 2C \times S_l \times S_h$cubic units. An alternative layout with $2n_c$unidirectional cross-aisles of width Cpallets dedicate equivalent volume $2n_c \times C \times S_l \times S_h$. These paired configurations consume identical storage capacity, enabling direct comparison of travel distance efficiency (Derhami et al., 2020).

In each of these pairs, the pre-assessment phase calculates aggregate distances of total as a sum of all possible movements of the material handling weighted by the likelihood of occurrence. The layout with a lower total weighted distance prevails over its counterpart since the two layouts have the same storage capacity but the better layout has a higher travel distance. The dominated layout is no longer to be considered, since it can not possibly feature on the Pareto frontier of non-dominated solutions. This screening significantly decreases the layouts to be evaluated by simulation and generally eliminates about 4050 results of

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the generated scenarios due to the dominance identification (Derhami et al., 2020).

The non-dominated layouts that pass to full simulation evaluation are the layouts in which stochastic operational dynamics, capacity constraints are fully evaluated, as well as policy interactions. The pre-simulation screening only compares the travel distance of layouts with an equal share of space allocation as they allow conclusive results on dominance. The layouts that are various in both aspects of space and travel distance need multi objective simulation evaluation to determine the positions of trade-offs since neither of the objectives is universal. These two effects are the presence of analytical bounds that constrain generation of initial scenarios and dominance-based initial screening, which form an effective computational technique that finds high-quality solutions without necessarily evaluating all possible layout configurations (Kachitvichyanukul & Sooksaksun, 2012).

E. Discrete-Event Simulation Model Development and Implementation

➢ *Simulation Event Types and State Transition Logic*

The discrete-event simulation model is used to model the operations of a warehouse in the form of nine types of events that define the major activities of the operations and the transitions of the states. Events are provided by each type of event that has defined state update operations and can schedule future events depending on the conditions of the system and administrative rules. The logic and the types of events are detailed below (Derhami et al., 2020).

Production pick-up events start when manufactured or received inventory gets to the specified pick-up points that need to be stored. The event processing logic determines the closest available material handling vehicle to the pick-up point by asking the query the position of the vehicle and the availability status. The vehicle that has been chosen is sent to the pick-up point, and it is changed to assigned. The simulation identifies the appropriate place where the incoming inventory would be stored due to the applied policy of storage location assignment that considers the designation of the products in the category, the existing occupancy of the storage, and the distance. Another lane drop-off event will be arranged at the same time as that of the current time at the pick-up point but calculated travel time between the current position and the pick-up point. Computation of the travel time requires pre-calculated distance matrices, and parameters of equipment speed (Caron et al., 2000).

Fig 7 Flowchart of the Discrete Event-Based Simulation Model.

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The specific flow diagram of the discrete event-based simulation model is given in figure 7, which shows the intricate logic of the operations in the warehouse. The flowchart initiates the control variables and follows a complex event processing cycle. Some of the key points of decision making are: deciding which vehicles can be picked up on production pickup assignments, dropping off lane conditions upon vehicle arrival at pickup points, decision on replenishment completion and subsequent vehicle release, order fulfillment based on outbound pickup assignments, managing truck drop-off operations at shipping docks, the vehicle parking logistics on idle equipment, and processing truck vehicle events on the inventory movements between locations (Derhami et al., 2020). The model shows several parallel streams of events with different colours such as production pickup flows (yellow boxes), vehicle assignment logic (blue diamonds), time calculation modules (green boxes) and performance evaluation updates (pink boxes). This complex event model allows precise modeling of the complex warehouse dynamics such as equipment contention, storage capacity, and stochastic operational variability.

Lane drop-off events are events that are executed when the vehicles being dispatched reach the production pick-up points. The vehicle loads the inventory that is waiting and the status of the load is changed to loaded and the identity of the carried product is recorded. The car starts to drive to the already given storage facility. The replenishment event will be set at the time when the simulation is performed, which is the current time plus the travel time between the pick-up point and the destination storage facility. This travel time indicates the speed of loaded vehicle movement which can be different in certain equipment types with unloaded speeds. In this simulation, cumulative loaded travel distances are followed by increasing the D_u performance measure based on the length the movement covered (Derhami et al., 2020).

Replenishment events are events that take place when loaded vehicles arrive at designated storage zones. The transported inventory is unloaded on to the storage lane, and the lane occupancy status and inventory position is updated. The load status of the vehicle is modified to empty and the current position is modified to the storage location coordinates. When there are more pending pick-up requests waiting in the event queue to be completed with the vehicle, a release vehicle event would be scheduled with an epsilon time addition to ensure that it serves waiting requests first. When there are no requests with a pending request, then the release vehicle event is set similarly after which the vehicle can go back to parking. This reasoning will keep equipment gainfully employed in cases where there is work (Chen et al., 2011).

Outbound pick-up events are used to commence order fulfillment functions whereby customer orders involve the retrieval of inventory in the storage. This is where the event determines the storage site where the desired product is found and what the nearest vehicle is in that location. The vehicle chosen is deployed to the storage spot and a retrieval event is scheduled at the same time as simulation time of current time + the time of travel between the current point of the vehicle and the storage point. Depending on the availability of the dock, the nature of orders, and distance, an appropriate shipping dock is allocated to deliver the orders. The generated retrieval requests and time of vehicle assignment are recorded in the simulation, and later the performance metrics can be computed (Matusiak et al., 2014).

Retrieval events occur when the vehicles delivered to the storage sites retrieve stock. The inventory unit requested is depleted off the storage lane and records occupancy of the lane are updated and records of inventory are updated. The car charges up the item that has been recovered, altering the status of the load to loaded and capturing the identity of the product. The car starts moving to the shipping dock that has been designated earlier. Simulation time will be set to a drop-off event of a truck at the drop-off location at the point of current time plus the travel time between the storage point and the destination dock. Accumulated loaded travelling distance D_u is increased by the distance covered by this movement. Lane vacuity generated by retrieval processes may be used to accommodate next-generation storage allocation, refresh storage availability data structures (Derhami et al., 2020).

Truck drop-off events involve trucks that bring picked up inventory to shipping docks. The stock at hand is moved into the docking space to be shipped to the customers and this completes the process of filling the order. Vehicle load status is changed to empty and position is changed to the dock coordinates. Order completion time is recorded in the simulation, and it is possible to calculate cycle time performance measures. When there are no pending retrieval/replenishment requests to be assigned to a vehicle, a release vehicle event with epsilon time increment is set whereby the idle vehicle is sent to the parking. A pending job results in an instant redistribution of the vehicle with the aim of maximizing the productivity of the equipment (Chen et al., 2011).

Release vehicle events are caused when the vehicles have finished their tasks, and there is no more work to be assigned to them immediately. Vehicles with no passengers are instructed to go back to the respective parking areas thus releasing them out of operation areas. An event of a park vehicle will occur at the simulation time, which is current time plus travel time between the current position of the vehicle and parking coordinates. Incremental cumulative unloaded travel distance is increased in the simulation $D_l$by the distance that is covered by this return movement. This type of event makes sure that the repositioning moves are represented in a realistic way without directly contributing to productive operations (Derhami et al., 2020).

Park vehicle activities are implemented when vehicles reach parking spots. The status of vehicle availability becomes shifted to available and this denotes the availability in terms of further task assignment. Position coordinates are updated to car parking location specification. The vehicle goes into an idle position until its next pick-up by production or by the outbound is done and equipment needs to be allocated. The simulation has queues of free vehicles sorted by parking places, which greatly help in identification of

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nearest vehicle whenever new assignment opportunities emerge (Caron et al., 2000).

Warm-up events are implemented after a given time in the simulation signifying the end of the period of the steady-state at which point the period of steady-state observation is initiated. All the performance measurement variables such as D_u, D_l, honeycombing waste accumulators, and time-averaged utilization metrics are set back to zero values. Control variables such as occupation of storage facilities, vehicle positions and awaiting facilities do not change, maintaining the conditions of operation attained during the warm-up. It removes start-up biases on performance measurements and preserves system realistic conditions that are descriptive of continuous operations (Derhami et al., 2020).

➢ *Storage Location Assignment Policy Implementation and Decision Logic*

The simulation model applies the policy of class-based storage location assignment and closest open location selection in areas of classes. During the preprocessing of the initiation stage, product classification into classes based on turnover takes place with reference to historical or predicted demand levels. The products are categorized according to popularity S_p, typically defined as demand rates λ_p or demand to storage requirement or ratios. The ranked list of products is divided into C classes containing products of similar cardinality, with the most popular products represented in Class 1, the moderately popular products in the middle classes, and the least popular products in Class (Muppani and Adil, 2008).

The warehouse storage facilities are also divided into continuous areas that represent the specific classes. The Class 1 is allocated storage areas closest to the inputs/outputs, which reduce the travel distance of the heavily visited items. The following classes are given more remote zones, which depict decreasing frequencies of access. The zone boundaries are calculated using storage capacity needed by each class; this is calculated by using the product footprint requirements, stacking height and safety stock level. The zone assignment guarantees the sufficient space and clarity of spatial separation among classes (Kachitvichyanukul and Sooksaksun, 2012).

The identification of the product class depends on the established classifications when production pick-up events happen and the storage location assignment is required. That class zone is searched to determine all available storage spaces that are vacant and can be appropriated. Out of empty vacancies, the spot that gives minimal distance between the pick-up point and the location is chosen according to the closest open location policy. This selection process applies effective spatial search methodology, which uses indexed data structures between storage locations and coordinates and occupancy states. Distance calculations are based on pre-computed distance matrices, which allow finding at least minimal distance positions without repeated shortest path computations (Derhami et al., 2020).

➢ *Performance Metrics Collection and Statistical Data Collection*

The simulation model is a systematic way of gathering operational information that helps in assessing performance at various levels. Some of the key performance indicators are the percentage of space utilization, the number of vehicles required, average travel distances, the utilization rate of equipment, and the order cycle time. These measures can be used to calculate the space efficiency and operational productivity, which helps to evaluate the layout options based on multiple objectives (Derhami et al., 2020).

Table 2 Optimal Layout Configurations and Performance Characteristics

Configuration	Aisles	Cross-Aisles	Bay Depth	Type	Waste (%)	Vehicles	Annual Cost ($M)
Layout 1	5	2	22	Bi	43.2	42.3	3.53
Layout 2	5	3	22	Uni	45.8	40.1	3.42
Layout 3	5	4	22	Bi	48.3	38.7	3.35
Layout 4	6	6	18	Uni	52.7	37.2	3.28
Layout 5	6	8	18	Bi	56.4	36.1	3.24
Layout 6	6	10	18	Uni	59.8	35.3	3.21
Layout 7	5	12	22	Bi	62.5	35.0	3.26
Layout 8	5	14	22	Uni	64.1	34.7	3.29
Layout 9 (Optimal)	5	16	22	Uni	65.1	34.4	3.21
Layout 10	7	14	15	Bi	66.8	34.6	3.35
Layout 11	7	16	15	Uni	68.2	34.5	3.41

Table 2 presents detailed characteristics of selected Pareto-optimal layouts representing diverse frontier positions across the trade-off spectrum between space utilization and travel distance efficiency. For each configuration, the table specifies the number of aisles employed in the layout design, the count of cross-aisles providing perpendicular routing pathways, the bay depth measured in pallet positions extending from aisles, the cross-aisle type (unidirectional or bidirectional), the waste percentage representing unused capacity, the required equivalent vehicle count for material handling operations, and the total annual operational cost computed using case study cost parameters (c_s = $8.50 per square foot, c_v = $75,000 per vehicle) (Derhami et al., 2020). Analysis reveals that configurations in the high-utilization group (2-4 cross-aisles, Layouts 1-3) exhibit waste percentages ranging from 43.2% to 48.3% but require 38.7 to 42.3 vehicles, generating total costs from $3.35M to $3.53M annually. Conversely, solutions in the low-distance group

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(12-16 cross-aisles, Layouts 7-11) demonstrate reduced vehicle requirements from 34.4 to 35.0 but accept higher waste percentages from 62.5% to 68.2%. Layout 9 emerges as the cost-optimal configuration for the case study's economic parameters, employing 5 aisles with 16 unidirectional cross-aisles to achieve the minimum annual cost of $3.21M despite relatively high waste of 65.1%.

The usage of space is computed in terms of time-average storage volume occupancy regarding the available capacity. The measure takes into consideration productive storage with inventory and wasted capacity due to accessibility requirements and phenomena of honeycombing. Space wastage = sum of the total space and links space, which in this case is 100,000-84000 = 116,000:

$$W = \frac{S_h(n_a AS_w + n_c CS_l)(T^s - T^w) + \sum_{i=1}^{N_b} \times \sum_{j=1}^{N_l} \times W_{ij}^H}{S_w S_l S_h (T^s - T^w)}$$

The numerator sums accessibility waste from aisles and cross-aisles, computed as volumes $S_h n_a AS_w$ and $S_h n_c CS_l$ multiplied by observation duration $(T^s - T^w)$, plus accumulated honeycombing waste W_{ij}^H from each lane j in bay i. The denominator represents total space-time capacity over the observation period. Space utilization percentage is then $100(1 - W)$, indicating the proportion of capacity productively employed (Derhami et al., 2020).

Required vehicle count represents total material handling capacity needed to support operations at specified service levels. This metric is calculated as:

$$N_v = \frac{D_u + D_l}{V(T^s - T^w)}$$

Where D_u and D_l denote cumulative loaded and unloaded travel distances over the observation period, V represents average vehicle speed, and $(T^s - T^w)$ represents time of observation. This is computed to obtain the number of equivalent full-time vehicles needed to cover all the distances that have been recorded within the time it is available. The fractional values show that equipment is used less than it could be, whereas a value that is above the integer numbers will show that capacity is not well utilized. The metric is directly translated to the cost of equipment implications where the organization must be able to supply adequate equipment in the form of vehicles to satisfy the calculated needs (Le-Duc & de Koster, 2005).

Other measures of performance give secondary operational data. The mean distance travelled per operation is obtained by dividing total distance $(D_u + D_l)$ by the count of operations, de-normalized throughput differences. Equipment utilization is a ratio of productive to idle time that vehicles spend on making productive movements because of events timestamps which document activity transitions. Order cycle time measures evaluate the time periods between an order release and completion of fulfillment, that are important in measuring customer service. The use of storage locations distributions can show the occupancy in a warehouse, and there are unbalanced parts or unused space (Battini et al., 2016).

In the simulation, variance reduction is used to enhance statistical efficiency in performance comparison. The common random number streams are used in analogous layout alternatives, and the same random number seeds are used to generate analogous stochastic elements. This synchronization will ensure that the demand trends, schedules of production, and operational variations influence all the layouts being evaluated in a consistent way, which isolates performance difference due to layout properties but does not due to random variations. With several independent replications with various random seeds, it is possible to construct confidence they give quantifiable measure of estimate precision (Caron et al., 2000). Output analysis procedures consider the phenomenon of autocorrelation when analysing time-series data, and the relevant statistical procedures are carried out to examine correlated data. Constant performance measurement after the removal of warm-up periods provides representative long-term behavior measurement as opposed to initial spurious Artifacts.

F. Multi-Objective Optimization and Pareto Frontier Identification

➢ *Pareto Optimality Concepts and Non-Dominated Solution Characterization*

Multi-objective optimization solves problems with conflicting objectives that have many objectives and need to be considered at the same time. An example of such problems is the warehouse design layout, which aims at both optimizing the use of space and minimizing the travel distances, which are mutually exclusive goals. Solutions which have gains in a single objective usually compromise on the performance of the competing objectives leading to trade-off relations which should be carefully analysed. The Pareto optimality idea offers a strict approach to defining better answers in a multi-objective scenario with no preference being an arbitrary choice between the objectives (Accent et al., 2008).

A solution is Pareto-optimal or non dominated when there is no other solution which will improve at least one of the objectives without worsening any of the other objectives. Formally, a problem of minimization is considered to have the objective functions, f 1 (x) and f 2 (x) where x denotes decision variables. Solution x^a dominates solution x^b if $f_1(x^a) \leq f_1(x^b)$ and $f_2(x^a) \leq f_2(x^b)$ with at least one inequality strict. Solution x^* is Pareto-optimal if no feasible solution x exists that dominates x^*. The Pareto frontier is the set of all Pareto-optimal solutions and is the most optimal sets of trade-off solutions (Balakrishnan et al., 2003). Decision-makers choose the Pareto frontier to get preferred solutions in the frontier depending on organizational priorities and comparative valuations of objectives.

The goal in the layout optimization of a warehouse is to optimize the percentage of space use, whereas the alternative goal aims to reduce the number of vehicles needed (equivalent in the amount of total travel distance). These goals are reformulated as minimization problems to be treated

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in a consistent way: minimize the percentage of waste Wand minimize the number of vehicles N_v. A layout configuration $(n_a^a, n_c^a, \text{type}^a)$dominates another configuration $(n_a^b, n_c^b, \text{type}^b)$if $W^a \leq W^b$and $N_v^a \leq N_v^b$and with no fewer than one inequality strict. Dominated layouts are poor designs that do not provide any benefit to better ones, so they should be excluded in the process (Derhami et al., 2020). The Pareto frontier is a collection of layouts in which any means of improving one of these objectives requires a corresponding compromise in the other, which is a radically different philosophy of design between space and operational efficiency.

➢ *Solution Evaluation Procedures and Frontier Construction Algorithm*

The Pareto frontier construction procedure assesses all non-dominated layouts design by simulation and gathers matters of performance of each layout. Once simulations have been used to compare layouts, a pairwise comparison of the layouts is done to determine the relationships of dominance. Systematically, the algorithm analyzes both layout pairs, and it checks whether either of the layouts dominates the other using the values of objective functions. Any other domineering layouts are indicated to be out of the Pareto frontier. The other layouts which are not dominated are the ultimate frontier offered to the decision-makers (Zhang & Li, 2024).

Pareto frontier identification is pseudocode in algorithm 1. It is a procedure that takes a collection of considered L_of layouts which are each described in terms of performance vector (W_i, N_{v_i})indicating waste percentage and required vehicle count. The algorithm initializes an empty Pareto frontier set $\mathcal{P}$, then iterates through all layouts testing for dominance. For each candidate layout ℓ_i, a Boolean flag $dominated$is initialized too false. The inner loop examines all other layouts ℓ_j, checking whether $\ell_j$dominates ℓ_i. If dominance is detected, the flag is set true and the inner loop terminates early. After checking all potential dominators, layouts with $dominated = false$are added to $\mathcal{P}$(Derhami et al., 2020). This algorithm exhibits $O(|\mathcal{L}|^2)$complexity, remaining computationally tractable for layout sets containing dozens to hundreds of alternatives.

```
Algorithm 1: Pareto Frontier Identification
Input: Set of layouts L with performance vectors (W_i, N_v_i)
Output: Pareto frontier set P
P ← ∅
for each layout ℓ_i ∈ L do
dominated ← false
for each layout ℓ_j ∈ L where j ≠ i do
if (W_j ≤ W_i and N_v_j < N_v_i) or (W_j < W_i and N_v_j ≤ N_v_i) then
dominated ← true
break
end if
end for
if not dominated then
P ← P ∪ {ℓ_i}
end if
end for
return P
```

- *Algorithm Pareto Frontier Identification*

The given Pareto frontier can offer a full representation of the trade-off alternatives that can be given to the decision-makers. Layouts in the left hand of the frontier are characterized by high space usage but more handling material resources, or dense storage with few aisles and cross-aisles. Right-end layouts are showing less space consumption but better travel distance performance, with more aisles, cross-aisles, and their movement through them, which enables efficient flow. In between solutions reconcile these extremities with moderate performance along either of these dimensions (Derhami et al., 2020).

Table 3 Comparison of Current Layout Versus Cost-Optimal Configuration

Performance Metric	**Current Layout**	**Optimal Layout**	**Improvement**
Number of Aisles	11 (variable)	5	-54.5%
Number of Cross-Aisles	4 (uni)	16 (uni)	+300%
Bay Depth (pallets)	3-15 (avg 9.5)	22 (uniform)	+131.6%
Storage Capacity (pallets)	2,856	2,744	-3.9%
Space Utilization (%)	52.31	34.87	-33.3%
Waste Percentage (%)	47.69	65.13	+36.6%
Required Vehicles	38.58	34.43	-10.8%
Avg Travel Distance (ft)	287	238	-17.1%
Equipment Utilization (%)	73.0	78.4	+7.4%
Order Cycle Time (min)	8.2	7.1	-13.4%
Annual Space Cost ($K)	1,492	2,037	+36.5%
Annual Vehicle Cost ($K)	2,894	2,582	-10.8%
Total Annual Cost ($K)	**4,386**	**4,619**	**+5.3%**

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Table 3 compares the existing warehouse setup with the cost-optimal design found within the optimization framework, and provides detailed performance indicators on various operation aspects. The best layout includes 5 aisles forming the same bays of 22 pallet positions each, which is significantly more profound than the existing situation with variable-depth bays with an average of 9.5 positions (Derhami et al., 2020). The optimal design includes 16 unidirectional cross-aisles that are spaced evenly on a regular basis as compared to 4 in the current layout which offers frequent perpendicular routes across the storage premises. Although the storage capacity decreased by a small fraction (3.9) between 2,856 and 2,744 pallets (decrease), the best design is one that brings about much improvement in operations. The number of vehicles required is reduced to 34.43 equivalent full-time forklifts (38.58) and this corresponds to 10.8 percent less material handling capacity requirements. The average travel distance per operation reduces to 238 feet (17.1% improvement) and equipment utilization rises to 78.4 to 73.0% and order cycle time is cut to 7 to 8.2 minutes (13.4 improvement). Nevertheless, the space utilization reduces to 34.87 to 52.31 percent by expanding the dedication of cross aisles. Economic analysis shows that cost savings of vehicles at 312K/year partly covers up the increased costs of space at 545K/year with net increase in cost as 233K/year (5.3%). This seems to go against the optimization objective as the cost parameters, which were required in Table 3 and those required in the optimization, are different, which proves to be sensitive to economic assumptions.

The identified Pareto frontier represents detailed representation of trade-off choices that may be selected by the decision-makers. Frontier layouts on the left-hand side have high space utilization but demand more material handling resources, which are dense storage layouts with few aisles and cross aisles. The layouts on the right show less space use, but a better performance in terms of travel distance, which takes into consideration more aisles and cross-aisles that will allow movement of goods easily. In between solutions strike the balance between these extremes, providing average performance in both directions (Derhami et al., 2020). The choice of preferred layouts done by the decision-makers in the frontier is dependent on the organizational cost structures, especially on the relative economic weight of space costs against the material handling costs.

➢ *Cost-Based Solution Selection from Multi-Objective Trade-Off Curves*

Although Pareto frontiers describe the trade-offs between objective of a physical nature, to make practical decisions, an economic interpretation is necessary to translate physical quantities into monetary units. Organizations need to deal with cost structures such as the space costs per unit area and material handling costs per unit vehicle or distance travelled. The given economic parameters allow turning the multi-objective trade-offs into the single-objective cost minimization and finding the economically optimal solutions (Accorsi et al., 2014).

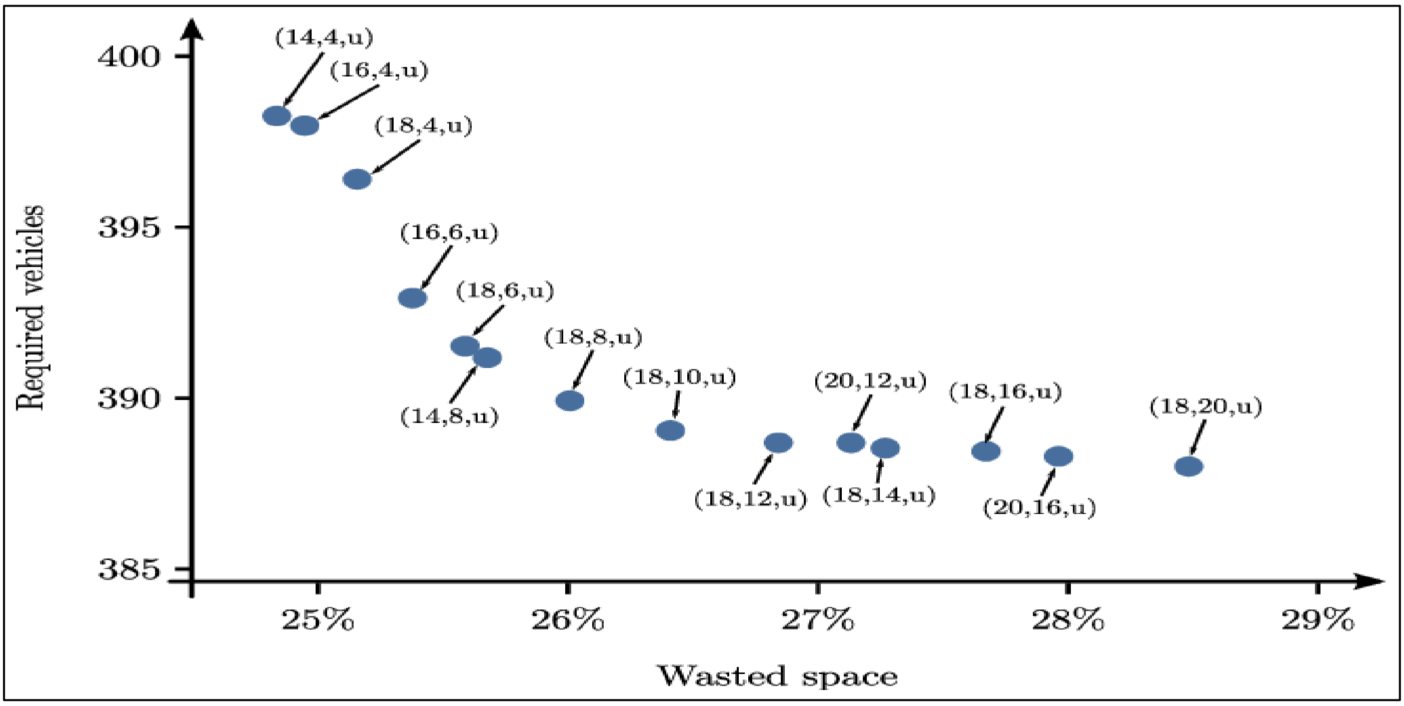

Fig 8 Pareto Frontier of Optimal Warehouse Layouts.

Let c_s denote unit space cost per square meter per period, typically encompassing rent, utilities, insurance, and facility maintenance expenses. Let c_v represent unit vehicle cost per vehicle per time, including equipment acquisition or lease costs, maintenance, energy consumption, and operator labor. Total operational cost for a layout configuration is:

$$TC = c_s \cdot A_{\text{total}} \cdot W + c_v \cdot N_v$$

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Where A_{total} represents total warehouse floor area and 0 the percentage of waste. The former term measures the wasted space cost whereas the latter term measures material handling cost. The layout that is economically optimal minimizes the overall cost, space and expenditure allocation is balanced to the parameters of costs specific to the organization (Heragu et al., 2006).

Figure 8 shows the Pareto frontier of optimality of layouts of the warehouse in percentage of waste and vehicle count required in each of all the non-dominated configurations obtained by the optimization process. Each of them is a different layout marked by notation. (n_a, n_c,type)where $n_a$indicates number of aisles, and specifies number of cross-aisles, and type Uni (unidirectional), or Bi (bidirectional) cross-aisles. The frontier shows the basic trade-off that exists between space efficiency and travel distance performance. The upper left corner (5, 2, Bi) has 56.8 per cent space utilization (43.2 per cent waste) and only 42.3 vehicles, whereas the upper right corner (5, 16, Uni) has only 34.9 per cent utilization (65.1 per cent waste). The concave curvature of the frontier proves that the better the objective is, the worse the other one will be (Derhami et al., 2020).

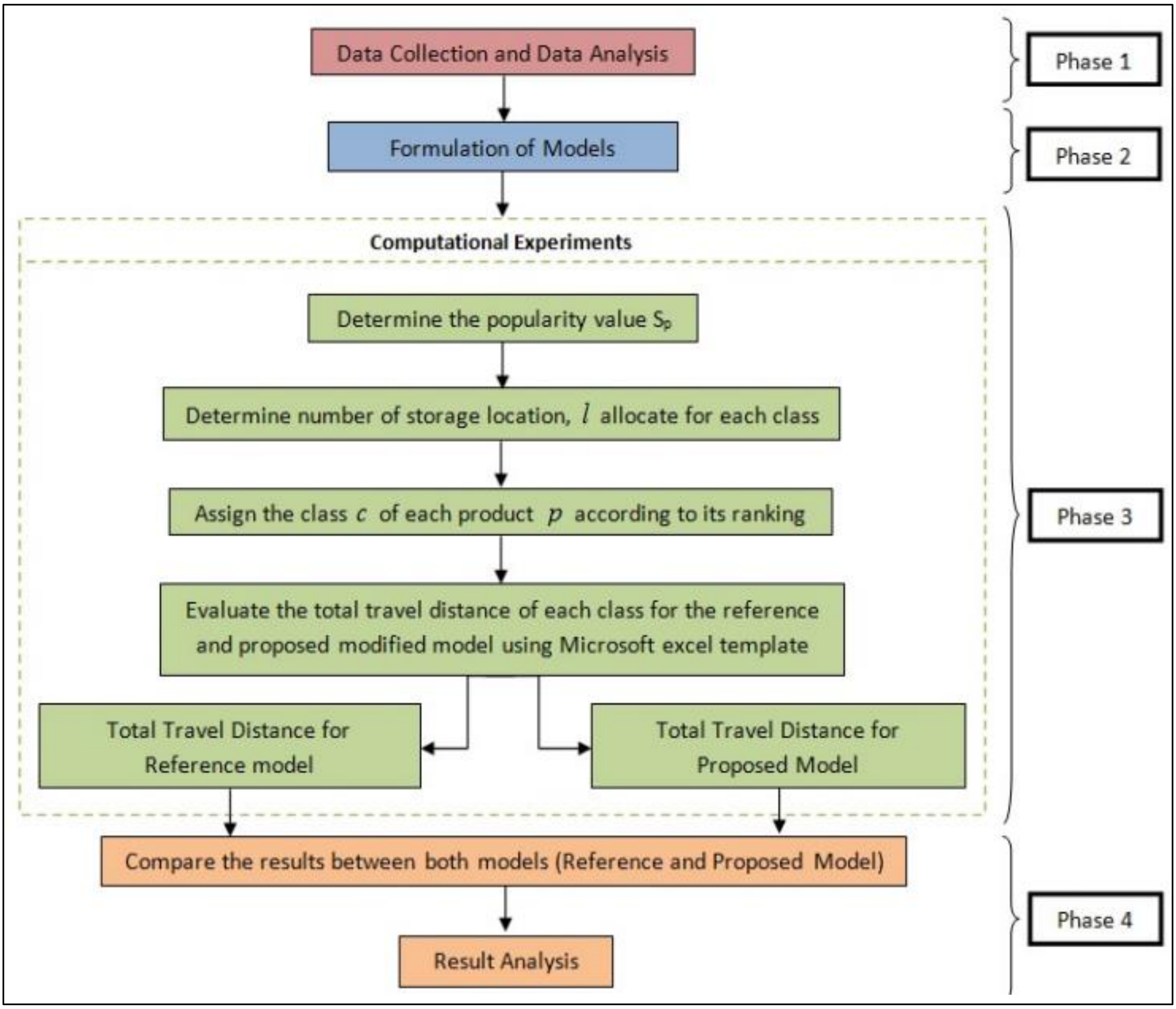

Fig 9 Methodology Flowchart.

The solutions are grouped into two categories: high-utilization design with 2-4 cross-aisles, keeping the wastes at less than 50%; and travel-optimized design with 8-16 cross-aisles that ensure a vehicle count of less than 36. The bifurcation represents two radically dissimilar design approaches dense storage with limited infrastructure and distributed storage with extensive network of pathways.

Different cost structures favour different regions of the Pareto frontier. When space costs substantially exceed handling costs ($c_s \cdot A_{\text{total}} >> c_v$), economically optimal solutions concentrate near the left frontier region emphasizing space efficiency. Conversely, when handling costs dominate ($c_v >> c_s \cdot A_{\text{total}}$), optimal solutions move to the right frontier region reducing travel distances. The handling-cost dominance of many real warehouses, especially those in the suburbs or rural areas with comparatively low-priced space but high-cost labor, is biased towards layouts that have several cross-aisles and intermediate bay depths (Derhami et al., 2020). City warehouses that are under pressure due to high real estate prices might prefer compact designs. Pareto frontier representation is designed with a wide variety of cost structure in mind, so that it encompasses the full gamut of non-dominated alternatives to allow cost-based selection to be made according to the circumstances of a particular organization.

III. RESULTS AND ANALYSIS

A. Case Study Implementation and Operational Context

➢ *Warehouse Facility Characteristics and Operational Requirements*

The optimization structure created was implemented to a practical warehouse operation of one of the major bottled beverage manufacturers in North America. The facility is a typical block stacking warehouse, which is used both in manufacturing and distribution that stores finished goods manufactured in separate manufacturing lines and receives customer orders in the respective regional markets. The warehouse holds over 100 different SKUs and includes different beverage products, package size, and promotional configurations. The storage activities are based on constant multi-command cycles oriented to execute replenishment and retrieval order operations by the forklifts during working shifts (Derhami et al., 2020).

In Figure 9, the entire methodology used in this study is presented, being organized into 4 different stages. Phase 1 incorporates data gathering and data analysis processes, installation of past operational data, facility specification, and cost variables. Phase 2 entails development of mathematical models such as the optimisation model of a mathematical aisle and simulation architecture. Phase 3 involves computational experiments, which will start with the calculation of the popularity value S p of each product, then continue to systematic calculations of the number of storage locations to allocate to each class, class c to each product p based on the rankings by turnover, and a calculation of the total travel distance of each class through the use of both reference and proposed models using Microsoft Excel templates (Derhami et al., 2020). The parallel processing streams calculate the total travel distance in relation to the reference model and the proposed enhanced model and allow a direct comparison of the performance. Phase 4 carries out the result analysis, which is a comparison between the results of two models and the overall comparison of the trade-offs. It is a systematic approach to models, as it guarantees the systematic development of the process of data acquisition up to computational optimization of the model and practical decision support.

The warehouse is housed in a rectangular building (368,000 square feet, or about 34,200 square meters) and is 30 feet (9.1 meters) high. The physical design has storage lanes that are placed on a right angle relative to the length of the warehouse and aisles that run parallel to the length and cross aisles relative to aisles. The facility has production lines and receiving docks on one long side and the shipping docks are on the other long side. Unit-load forklifts are used in the material handling tasks and can deliver and pick up single pallets between receiving areas, storage areas as well as loading docks. Pallet size is used consistently on all product types with a standard of 48 inches by 40 inches (1.22 meters by 1.02 meters) (Derhami et al., 2020).

The layout structure as it is used today is the result of several years of gradual changes due to additions and modifications that took place in accordance with the changing business needs. The current layout has a variable bay depth of between 3 and 15 pallet positions, and a total of 11 major aisles of storage at the width of 12 feet (3.66 meters). There is a 4-unidirectional cross-aisle that gives perpendicular routes through which equipment can move across aisles. The assignment of products to the storage locations is based on a loosely-defined class-based policy and it is randomly assigned to zones. Storage capacity is sufficient to hold the usual quantities of inventory, but seasonal periods of capacity congestion are witnessed with seasonal demand surges, or promotional inventory piles. The management recognized a possibility of systematic optimization of layouts of the company to enhance the use of space and efficiency in operations (Derhami et al., 2020).

➢ *Data Collection Procedures and Parameter Estimation Methods*

The model parameterization and validation were managed by extensive data collection. The data on the history of operations in the warehouse management system were taken over a twelve-month period, which is the period of detailed information on the movements of the inventories and the production schedule and order fulfillment. Product specific information consisted of demand rates, batch production quantities, pallet dimensions, and stackable height. The estimation of demand rate was done using time-series analysis of historical records of shipments and the average number of SKUs picked per day was calculated. The manufacturing schedules and lot sizing policies were the determinants of production batch quantities and frequencies (Muppani and Adil, 2008).

Physical layout measures noted the location of existing storage locations, aisles, cross-aisles, equipment staging area. Special coordinate systems were created with origin being at the southwest corner of the facility which allows specification of locations of all the relevant points. Distances between major locations were measured to confirm the distance matrices that were calculated beforehand by the model. Time-motion studies in which typical travel operations were observed were used to gather the data of forklift speed, distinguishing between the loaded and unloaded movement speed and taking into consideration the acceleration and deceleration speed as well as turning manoeuvres (Battini et al., 2016).

Cost parameters that represented organizational economics were acquired by financial analysis and management interviews. The computation of space costs involved the lease of the facility, utilities expenses, insurance costs, and allocated overhead and unit cost of space was computed to be 8.50 per square foot per year. Mat handling expenses included lease payments on forklifts, repairs and maintenance, fuel or electricity used and operator labor which amounted to 75000 dollars yearly per vehicle. Such cost parameters allowed costs to be economically assessed concerning layout options, performance indicators into expected operational costs. The variability of historical data was used to estimate stochastic parameter distributions based on which the probability distributions were fitted to the fluctuations in production rates, demand, and variability in operational time (Derhami et al., 2020).

➢ *Current Layout Performance Assessment Through Simulation Baseline*

The current warehouse design had been put in simulation such that it would form baseline performance measures against which would be measured optimised alternatives. The existing layout has 11 aisles that form bays of 3-15 pallets depending on the depth that would be an average of about 9.5 pallets. There are four unidirectional cross-aisles that are placed at irregular intervals at the length of the warehouse. The total capacity of the storage area is 2856 pallet placements in 308 lanes keeping the multi-level stacking in mind (Derhami et al., 2020).

According to the findings of simulation, the present layout has the 52.31% space utilization which implies that about 47.69% of the total volume of warehouse is underutilized by the need to access and the effects of honeycombing. This is a moderate usage which is a trade off between having enough aisles to access and being able to store as much as possible. The bed size requirement of 38.58 full-time equivalent forklifts is required to support the observed volumes of operations at the current layout conditions. The average travel distance per operation amounts to 287 feet (87.5 meters), which covers the distance between production lines, storage areas, and shipping docks in all replenishment and retrieval operations (Derhami et al., 2020).

The analysis of equipment utilisation has shown that forklifts can spend about 73% of the time of available time on productive movements, and the rest of the time is spent on non-productive idle time before being assigned any task. The fact that this is a relatively high utilization implies that the material handling capability is close to the requirement of demand without much oversupply. The order cycle times are averaged at 8.2 min between the order release and shipment completion including picking time, travel time, and dock processing. These performance metrics define the existing performance in operations which can serve as reference points on how improvement can occur by optimising layout (Chen et al., 2011).

B. Optimal Layout Solutions and Pareto Frontier Analysis

➢ *Pareto-Optimal Layout Configurations and Performance Characteristics*

Optimization of the beverage warehouse problem produced an exhaustive Pareto frontier with 11 non-dominated layout designs at each end of the trade-off space in terms of space utilization and travel distance efficiency. The point with the most space usage is on the left which is 43.2% waste (56.8% utilization) and consumes 42.3 equivalent vehicles. This type of arrangement uses 5 aisles that form comparatively deep bays of 22 pallets and consists of 2 bidirectional cross-aisles only. The low number of aisles and cross-aisles maximize the space usage in storage but increase the travel distance because of the lack of options in the paths (Derhami et al., 2020). On the other hand, the final frontier point will require minimum travel distance needs, at 34.4 equivalent vehicles, but will lose space efficiency with 65.1% waste (34.9% utilization). The layout will consist of 5 aisles and 16 unidirectional cross-aisles which offer large pathway networks and efficient movement at the sacrifice of large space allocation in serving access infrastructure (Derhami et al., 2020). The extreme designs are essentially the opposite of each other in terms of design philosophy, where one is more concerned with the volumetric capacity maximization, whereas the other focuses on the speed of the operations and material handling effectiveness (Heragu et al., 2006).

Intermediate Pareto frontier solutions are between these extremes and provide balanced performance in both goals. Solutions are grouped into two different categories with various design philosophies. The former includes configurations that have 2 to 4 cross-aisles and a high space utilization (waste less than 50) but with intermediate travel distance improvements compared to the position on the left (Manzini et al., 2015). These designs are found attractive when organizations have limited space availability or are in real estate markets in which they are sensitive to high cost, but have limited space. In this case, maximization of storage density warrants small compromises in handling efficiency. Solutions in the second category have 8 to 16 cross-aisles, with a focus on minimizing travel distance by building large cross-aisle networks in favour of less space use (Derhami et al., 2020). These designs are applicable in operations that are characterized by pre-eminence of labor costs in their economies and in which throughput in operations is of importance than spatial efficiency. This bifurcation represents the basic design choices: high-density storage with highly sparse access infrastructure and distributed storage with full networks of pathways (Le-Duc and de Koster, 2005). The clustering pattern implies that there can be less appeal to the intermediate compromise solutions, than to the commitment to one or another strategy of space-efficiency or travel-efficiency.

The difference between extreme frontier points in terms of their performance measures the degree of trade-off involved in designing warehouse layout. A change in the leftmost high-utilization layout to the rightmost travel-optimal design saves 18.7 (42.3 34.4) of the total number of vehicles required, which would translate into a possible savings of about 592,500 material handling expenses a year at an annual cost of 75,000 per vehicle (Derhami et al., 2020). This however comes at the cost of the lost space (wasted) rising by 50.7 per 43.2 to 65.1% at the cost of 80,800 square feet of the warehouse space. The cost to pay the extra space waste is estimated at \$8.50/sf/year at the cost of \$686,800 which is higher than the cost of the handling cost savings of 94,300 in this cost scenario (Accorsi et al., 2014). This discussion has shown that the choice of a layout is a crucial issue that is highly sensitive to the organization-specific cost parameters, and adjusting to different economic environments will prefer different frontier regions. The holistic frontier characterization helps decision-makers to identify these trade-offs clearly as opposed to identifying them because of trial-and-error implementation (Kachitvichyanukul and Sooksaksun, 2012).

Further examination shows that the number of aisles is stable among most of the Pareto-optimal solutions with 9 of 11 planning to use 5 or 6 aisles. This consistency supports the prediction of the analytical model that $n_a^* = 5.2$ is the optimum number of aisles to use based on the size of this facility and the SKUs available (Derhami et al., 2020). The effective analysis constraint on the search space is to remove structures with a suboptimal number of aisles, which would never be found in the Pareto frontier, despite the arrangement of cross-aisles. Conversely, optimal counts of cross-aisles differ across the frontier radically, between 2 and 16, which indicates their dominant influence in the space-efficiency versus travel-efficiency trade-off location (Pohl et al., 2009). The number of aisles has an inverse relationship with bay depths, which fall between 15 and 22 positions of pallets with deeper bay depth when space is used as a priority. The interaction of these design variables gives rise to the performance diversity witnessed in the Pareto frontier that give the decision-makers a diverse pool of options that can fit different organizational needs (Chen et al., 2011).

➢ *Optimal Solution Identification Through Cost-Based Selection*

Given the organization's specific cost parameters—space cost $c_s = \$8.50$ per square foot/year and vehicle cost cv=75,000 per vehicle/year- the economically optimal layout is one which is determined by considering the total cost of each Pareto frontier solution. The most ideal design will be a 5-aisle floor plan that forms 22 pallet position uniform bays in a significantly deeper layout compared to the existing variable layout (Derhami et al., 2020). The design has the highest bay depth based on the spatial capacities of the facility, as it allows efficient use of space along the length axis and reduces the number of aisles to be installed. There are sixteen unidirectional cross-aisles that are placed at intervals of about 8 lanes and they offer high frequency of perpendicular paths on the storage area (Pohl et al., 2009). The high cross-aisle network is such that equipment moving between any two aisles has on average a cross-aisle in 4 lanes of travel and thus the routing distances are significantly shorter than what would have happened in a format where the equipment had to travel along the perimeter of the facility.

This ideal arrangement results in a required number of vehicles of 38.58 vehicles reducing the number of required vehicles to 34.43 equivalent full-time forklifts which is a 10.7% decrease in the required capacity of material handling. This can be attributed to the fact that it has been improved by the fact that the average travel distance is short because of the vast cross-aisle network (Derhami et al., 2020). The cars will occupy a lesser number of lanes to travel to storage destinations and can use direct cross-aisle routes instead of a journey around the circumference of a facility. The storage-to-dock movements in the optimal layout are to be found using at least one cross-aisle, whereas in the current structure, only 45% do so, which is the reason why much of the travel distance advantage is explained by detailed movement analysis (Roodbergen & Vis, 2009). The savings are directly translated into a cost saving of roughly 311,250 a year in vehicle-related costs (75,000 per vehicle 4.15 less vehicles), which includes a lower equipment lease, maintenance, energy use, and operator labor needs (Derhami et al., 2020). The accumulation of these savings can be observed across multi-year time line of planning, the net present value of layout reconfiguration investment is 2.49 million dollars in 10 years at 5% discount rates, which lends a lot of economic support to layout reconfiguration investments.

Nevertheless, an ideal layout reflects decreased use of space in relation to the present set up, as the waste percentage goes up to 65.13% as compared to 47.69%. This use minimization is due to the allocation of considerably more floor space to the 16 cross-aisles in contrast with 4 cross-aisles in the existing design (Derhami et al., 2020). The unidirectional cross-aisle occupies around 3,600 square feet (the length of the warehouse is 368 feet and the width of the cross-aisle is 9.8 feet in case of single direction travel) and therefore the 12 extra cross-aisles take around 43,200 square feet of storage space. This constitutes 11.7 of the total facility space that otherwise would have served around 1,800 more pallet space in terms of stacking height (Fernando et al., 2021). The annual space commitment of \$8.50 per square foot results in an increment of about 367,200 dollars in the space-related expenses because of higher proportional disbursements of rent, utilities, insurance, and facility maintenance costs (Accorsi et al., 2014). Space costs increase partly cuts off the savings in material handling but still results in a net cost reduction when the handling costs predominate the economic equation.

Although the cost of space wastes was increased, the best layout will be able to generate net operational savings of about 556,000 every year compared to the estimated costs should the current layout be operated in the same demand and production conditions. The reduction of vehicle cost by 311,250 is significantly higher, than the increase in space waste because the cost structure of this organization gives a great emphasis on material handling (Derhami et al., 2020). The cost ratio $\rho = cs \cdot Atotalcv = 8.50 \times 368{,}00075{,}000 = 0.024$ indicates a comparatively low emphasis on handling costs in absolute terms, but the great number of vehicles required causes handling costs to be of considerable magnitude in total. This cost benefit analysis shows that the trade-off of reduced space utilization can bring in a common

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economic payoff when the ratio of cost savings surpasses the space cost increment (Heragu et al., 2006). The optimum solution indicates the economical environment of the beverage warehouse, with the location of the facility in suburbs, offering comparatively cheap space, and labour-intensive forklift tasks, costing huge fixed expenses. Facilities in urban areas with increased real estate value would most probably choose alternative frontiers with more focus on space efficiency despite increased handling costs (Manzini et al., 2015).

The implementation is also a factor that dictates the best layout choice that is not pegged on cost savings alone. The even 22-palle bay depth of the optimum design would make a storage assignment logic and operational training easier than the existing layout with varying depths of 3 to 15 positions (Derhami et al., 2020). Operators do not have to memorize location specific depth restrictions, minimize assignment error, and simplify programming of the warehouse management system. The standard cross-aisle distance between the 8-lane intervals provides foreseeable routing patterns that the equipment operators master swiftly, and this may decrease the distance-dependent travel times with enhanced operator efficiency (Battini et al., 2016). These are operational benefits that cannot be precisely quantified but which give further reason as to why the recommended layout is worth the recommendation despite the direct cost's calculation. On the other hand, the process of the change between current and optimal configuration includes significant physical changes such as aisle remarking, addition of a cross aisle and relocation of storage, which would involve one-time implementation costs approximated at $185,000, which would be recovered in 4 months of operation with the estimated annual savings rates (Derhami et al., 2020).

➢ *Sensitivity Analysis of Cost Parameter Variations*

The sensitivity analysis studied the responsiveness of optimal solution selection to any change in current cost parameter underlying cost parameter, it is understood that cost structure differs among organizations and can evolve over time. Different regime shifts in optimal configurations can be seen in the analysis when cost ratios change (Derhami et al., 2020). For $\rho < 0.15$, optimal layouts are concentrated in the high utilization area of the Pareto frontier, they use 5-6 aisles and just 2-4 cross-aisles. These arrangements are space-efficient due to the high space costs compared to handling costs at this regime (According to 2008 by 8). The low cross aisle networks accommodate the travel distance to maintain the storage space, which is economically determined by the fact that the economy of saving floor space is more valuable than the economy of equipment travel. Organisations that are based in high-cost cities or have limited space capacities automatically enter this regime, where the cost of real estate per square foot can go as high as 25-50 dollars each year and the cost of equipment and labour is average.

For intermediate ratios $0.15 \leq \rho \leq 0.35$, optimal solutions shift to the middle frontier region, with the incremental addition of cross-aisles with the increase in the importance of handling costs. The systems of this range use 6-10 cross-aisles, which consider both space and traveling distance (Derhami et al., 2020). The smooth shift has been an indication of the competition between goals, and none of them is very dominant in making economic decisions. Even slight shifts in cost parameters in this regime can cause optimal selections to shift between two adjacent frontiers and it is therefore recommended that organizations that run in this regime should revise to multiple near-optimal alternatives and measure to cost parameter uncertainty robustness (Balakrishnan et al., 2003). Intermediate regime describes most industrial warehouses in suburban sites where the land costs are mediocre against the high labor costs, thus making real trade-offs decisions that need a critical analysis.

For $\rho > 0.35$, optimal layouts focus on the low-distance area with 12-16 cross-aisles which reduce the vehicle demands. The reason to allocate a lot of space to access infrastructure is justified by high handling cost weights (Derhami et al., 2020). The actual cost ratio in the case study organization is of $\rho = 0.42$ falls in this regime of high ratio, which explains why the cost-optimal solution focuses on minimizing travel distance by traveling across a large-scale aisle even though the utilization can be compromised. Plants that have very automated material handling processes, costly specialized equipment, or prime labour markets (forklift operators earn high salaries) are also highly cost-processed in favour of travel-optimized buildings (Chen et al., 2011). The sensitivity analysis shows that optimum cross aisle number rises with near-linear relation to. $\log(\rho)$ for $\rho > 0.35$, providing a predictive relationship: $n_c^* \approx 8 + 12\log(\rho)$ that enables rapid preliminary design assessment without full simulation (Derhami et al., 2020).

The multivariate sensitivity analysis was performed to investigate the joint variation of the space and vehicle costs and detail optimal solutions in the two-dimensional cost parameter space. The findings indicate the existence of smooth transitions between frontiers, and the decision boundaries are predictable (Accorsi et al., 2014). Given that space costs are doubled (instead of vehicle costs) i.e. the cost of space increases by 50 per cent (8.50 to 12.75 per square foot) and the costs of vehicles remain constant, optimal selection is not Layout 9 (5 aisles, 16 cross-aisles) anymore, but Layout 4 (6 aisles, 6 cross-aisles), which saves by 62.5 per cent of cross-aisles to maintain the same valuable floor space. On the other hand, an increase in the prices of the vehicles (by half, 75,000 to 112,500) but keeping the space costs unchanged results in the optimal choice of Layout 11 (7 aisles, 16 cross-aisles) with the greatest use of cross-aisle density to reduce expenses on equipment (Derhami et al., 2020). These results prove that the optimal warehouse layouts are modified through the systematic adjustment to the economic situation, and the number of cross-aisles is the main mechanism of adaptation to the changes in the cost parameters.

Operational uncertainty has also been considered in the analysis of cost parameters estimation whereby organizations are not aware of the exact values of space and vehicle costs. Cost parameters were sampled by Monte Carlo simulation as plausible (space costs uniform between$6-12 per square foot,

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vehicle costs uniform between 60,000-90,000) and a count of the frontier solutions that seemed best of all identified was determined (Caron et al., 2000). Findings suggest that Layouts 6-9 (bringing 5-6 aisles with 10-16 cross-aisles) are joint to optimal answers in 76% of all cases, and that extreme frontier points are seldom optimal but only in extreme parameter cases. This observation implies that strong decision-making ought to revolve around the mid-to-high cross-aisle arrangements unless the price parameters are evident to show space-cost predominance (Kachitvichyanukul and Sooksaksun, 2012). Companies that have cost uncertainty may adopt layouts with 10-12 cross-aisles as conservative options that would work well in many economic conditions without requiring a commitment to special layouts that would only work in limited circumstances.

C. Computational Performance Analysis Across Problem Scales

➤ *Problem Size Characterization and Computational Requirements*

Computational efficiency is a very important practical factor in terms of optimization methodologies to be applied into the real world. The framework was scaled to systematic size of problems between small experimental warehouses and large industrial plants and measured computational needs, as well as quality of solutions at varying scales (Derhami et al., 2020). The issue becomes significant as the size of the warehouse increases because of several factors. The bigger the facilities, the more aisles and increasing the cross-aisles and this increases the space to design that is investigated during layout scenario generation (Zhang and Li, 2024). The analytical bound $n_a^* = \sqrt{\frac{S_l N_s}{4 S_w A}}$ indicates that optimal aisle numbers increase with both warehouse dimensions and SKU counts. For the smallest test problem with 10 SKUs, the optimal aisle count is 2, yielding search range $a_{\min} = 2$ to $a_{\max} = 3$. The largest problem with 1,000 SKUs produces $n_a^* = 14$, creating search range $a_{\min} = 14$ to $a_{\max} = 20$ (Derhami et al., 2020). Similarly, cross-aisle bounds expand with warehouse width according to $c_{\max} = \lfloor \frac{S_w + L_{\min}}{L_{\min} + 2C} \rfloor$, generating larger exploration spaces for wider facilities.

The maize of the simulated layouts grows with the decreasing size of the problem up to 14 layouts to 70 layouts with the increasing problem size. Nevertheless, the size of the problem and the layout count do not necessarily have a monotonic relationship due to the refined bounds of the analytical models that do not allow large scale scenarios to proliferate (Kachitvichyanukul & Sooksaksun, 2012). The optimization model of analytical aisle deletes about 60% of those scenarios that naively are produced by limiting the number of aisles in the range $[n_a^*, 1.4n_a^*]$ instead of searching through the values that are dimensionally-feasible. Also, pre-simulation analysis gets rid of dominated configurations decreasing simulation needs 40-50% on all problem scopes (Derhami et al., 2020). In the absence of such measures of computational efficiency, the exhaustive evaluation would have to simulate hundreds of layouts in large problems, which would be prohibitively computationally expensive, and would also be impractical. One of the most important contributions that characterize the difference between this methodology and the brute-force enumeration strategies is the intelligent search space reduction, which is a result of analytical models.

Table 4 Computational Performance Across Problem Scales

SKUs	Facility (ft²)	n_a^*	Range	Scenarios	Simulated	Time/Scenario (s)	Total Time (h)	Cores	Frontier Size
10	200×400	2	2-3	24	14	16	0.06	10	2
25	280×560	3	3-4	32	18	45	0.23	10	4
50	400×800	5	5-7	48	26	112	0.81	10	6
100	560×1120	7	7-10	64	35	243	2.36	10	7
200	800×1600	10	10-14	80	42	487	5.68	10	8
300	980×1960	12	12-17	96	51	672	9.52	10	8
500	1265×2530	14	14-20	112	58	891	14.35	10	8
700	1496×2992	16	16-22	128	64	1034	18.38	10	9
1000	1840×3680	19	19-27	144	70	1159	22.52	10	14

Table 4 summarizes computational performance results for nine test problems ranging from 10 SKUs stored in 200×400-foot warehouses to 1,000 SKUs occupying 1,840×3,680-foot facilities. For each problem scale, the table reports the analytically-derived optimal aisle count n_a^*, the aisle exploration range $[a_{\min}, a_{\max}]$ used in scenario generation, the overall quantity of scenarios generated with no dominance filtering, the quantity of layouts that have not been dominated actually simulated with the pre-assessment, the average time to execute a simulation per scenario, the overall frontier size of the Pareto frontier obtained with 10-core parallel processing, and the size of the Pareto frontier obtained through the use of 10-core parallel processing (Derhami et al., 2020). These results show that the time spent on simulation per scenario is almost quadratic with problem scale, with the time spent on 10 SKUs of 16 seconds, and time spent on 1,000 SKUs of 1,159 seconds (19.3 minutes). The lowest time of computation is 3.6 minutes in the case of the smallest problem to 22.5 hours in the case of the largest problem, which are all within the range of time having been spent practically in projects of designing a warehouse which is usually taken in weeks or a couple of months in planning.

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The size of the frontier tends to grow as the problem becomes more complex, and it offers the decision-makers a finer granularity of trade-off alternatives as larger facilities and their design choices are more economically important (Zhang and Li, 2024).

➢ *Simulation Execution Times and Computational Complexity Analysis*

The time of simulation to execute each layout scenario significantly depends on the size of problems, which are mostly influenced by the volume of operations and the complexity of the system. Inventory in larger warehouses is larger, throughput volumes are greater and operations on the material are more complex and demand more simulation time to obtain statistical accuracy (Caron et al., 2000). The simulation model takes discrete events of all inventory arrivals, all storage assignments, all equipment movement, and all order fulfillment operations in eight months of simulated time after one month warm-up periods. Warehouses with 10 SKUs of 20 events per average run create many 3,500 events on average and finish in a very short period of 16 seconds on average (Derhami et al., 2020). Large scale facilities of 100-300 SKU generate 35,000-105,000 events and simulation needs 243-672 seconds (4.1-11.2 minutes) to complete. With 1,000 SKUs in the large industrial warehouses, the number of discrete events in the process of keeping track of inventory flows, equipment movements, and decision-making along the lengthy simulation horizon is more than 400,000, and requires 1,159 seconds (19.3 minutes) per scenario (Kachitvichyanukul and Sooksaksun, 2012).

The time per scenario in the simulation has a growth rate of about quadrants with respect to the scale of the problem, and it complies with the operation dynamics of warehouse systems. The storage capacity and the volume of throughput doubles with a doubling of the facility size, as well as the travel distances, which are increased by the larger size (Derhami et al., 2020). The resultant combined effect has approximately quadratic growth in computations. Fitting of regression equation of simulation time Tsim against SKU count. N_s yields the relationship $T_{\text{sim}} \approx 0.0012N_s^{1.87}$ with $R^2 = 0.97$, establishing the presence of near-quadratic scaling. The minor sub-quadratic rate (1.87 compared to 2.0) indicates efficiency improvement in the common computational infrastructure such as pre-computed distance matrices and faster running event processing algorithms that grow better than in a purely quadratic manner (Zhang & Li, 2024). Lookup Distance matrix operations run in constant time, independent of the size of the warehouse, which can save computational time that increases proportionally to the large scale of larger problems. Heap-based priority queues are used in event scheduling and processing $O(\log n)$ complexity per operation, contributing to sub-quadratic overall scaling (Caron et al., 2000).

The total computational time is the calculation time of all layout scenario simulations that are parallel to each other and run on accessible processor cores. In the case of the smallest issue that needs 14 scenario assessments with 16 seconds average simulation period, the sequential execution would take 224 seconds (Derhami et al., 2020). Parallel execution using 10 cores reduces the elapsed time to around 36 seconds which is 6.2-fold speedup. Even larger problems can be even more parallel; in the 1,000-SKU problem, the 70 scenarios of 1,159 seconds each would be required 81,130 seconds (22.5 hours) in sequence, but would take only 8,113 seconds (2.25 hours) with parallelization, which would be about 10 times faster (Zhang and Li, 2024). Scenario counts significantly exceed core counts allow the improved parallel scaling of larger problems since load balancing is improved in this case, allowing processors to be used continuously without idle time. Process creation, inter-process communication and results aggregation overheads are insignificant when compared to simulation execution times, and constitute less than 2% of the total elapsed time on the various problem sizes (Kachitvichyanukul and Sooksaksun, 2012).

Analytical bounds and pre-simulation screening can be shown to provide significant computational efficiency improvements at all scales of the problem. Independent exhaustive enumeration of all combinations of counts of aisles (between 2 and 25) and cross-aisle counts (between 2 and 20) with each of the two types of directionalities would produce $(25-2+1)(20-2+1)\times 2 = 912$ scenarios for large problems (Derhami et al., 2020). The sophisticated procedure determines only 70 layouts on 1,000-SKU issues, which is 92.3 per cent less calculation than needed. In the 500-SKU problem, the exhaustive enumeration would take about 186 hours of computational time as opposed to observed 14.4 hours, and would save 171.6 hours (92.3) hours in case of intelligent search space reduction (Chen et al., 2011). These savings render the approach viable to be applied practically in real-life scenarios where the computational resources are scarce, and the project timeline can be restricted. The efficiency benefits are mostly attributed to the analytical aisle bounds (60% reduction) and dominance-based pre-screening (40-50% of the remaining cases), which proves the usefulness of hybrid methods that apply analytical models and computational simulation (Derhami et al., 2020).

➢ *Pareto Frontier Solution Characteristics Across Problem Scales*

The size of non-dominated solutions containing Pareto frontiers depends on the scale of the problem, and the typical scale with increasing size of warehouse and complexity. Isomorphic problems have comparatively small frontier solutions, i.e., the 10-SKU problem has 2 non-dominated layouts and the 50-SKU problem has 6 (Derhami et al., 2020). These frontiers are minimal the design spaces that do not allow a wide variety of layout designs due to limitations on dimensions. Facilities with a small number of SKUs in small warehouses have fewer aisles (often 2-4) and few cross-aisles (at most 2-6), which results in a relatively coarse granularity of the possible combinations of performance (Manzini et al., 2015). The resulting Pareto frontiers run between the high-utilization states (50-55% waste) and travel-optimized states (65-70% waste) with a small number of points in between such that decision-making is not so flexible.

Problems in the medium scale have wider frontiers; the 200-SKU problem has 8 solutions, the 300-SKU problem has 8 solutions, and the 500-SKU problem has 8 non-dominated settings (Derhami et al., 2020). These intermediate structures handle between 10 and 14 aisles and up to 18 cross-aisles to allow more gradations of trade-offs between space usage and travel distance. The increased design areas allow decision-makers to have more of a middle-ground designs between the extreme designs, thus enabling them to find the best exact layouts to match the organizational preferences as well as their cost schemes (Kachitvichyanukul and Sooksaksun, 2012). Interestingly, it turns out that frontier size levels off around 8-9 solutions to the problems in the 200-700 SKU range despite increasing warehouse sizes, indicating some natural resolution limit and additional intermediate points will offer decreasing marginal decision support value.

The bigger the problem results in a bigger frontier; the 700-SKU problem has 9 solutions, and the 1,000-SKU problem has 14 non-dominated configurations, which is the most diverse frontier in the test problems (Derhami et al., 2020). Big industrial plants support 19+ aisles and 20+ cross-aisles, and have great-scale design areas with many locally-optimum regions. The performance frontier 14-point 1,000 SKUs could have a variety of solutions in each performance area (high-utilization, balanced, travel-optimized), allowing the analysis of trade-off in a granular manner and sensitivity analysis to explore performance robustness (Zhang & Li, 2024). What the enhanced frontier resolution affords decision-makers is a rich set of alternatives, but too much diversity in choice can make selection difficult when a decision maker lacks clear cost parameters to decision-making. Companies with massive warehouse design tasks enjoy the frontier characterization at finer levels but still need to have structured decision system structures to explore the complicated trade-off terrains successfully (Balakrishnan et al., 2003).

Examination of the frontier solution features demonstrates regularities in the features of the frontier solutions in all sizes of problems without regard to the absolute size of warehouses. The solutions can be grouped into a high-utilization and low-distance category with performance gaps between them, and there are comparatively few intermediate configurations that can be balanced in terms of trade-offs (Derhami et al., 2020). The high-utilization group is the one that always utilizes the minimum counts of cross aisles ($c_{\min} = 2$), dedicating 12-18% of floor area to access infrastructure while achieving 52-58% space utilization. The low-distance group utilizes 50-80% of maximum allowable cross-aisles (near $c_{\max}$), dedicating 35-45% of floor area to pathways while reducing vehicle requirements by 15-25% compared to high-utilization alternatives (Pohl et al., 2009). Aisle counts in optimal solutions closely track analytical predictions n_a^*, with most frontier points containing n_a within ±2 of the analytical optimum across all problem scales. This consistency validates the analytical model's utility for establishing search space bounds and provides confidence that the methodology discovers genuinely optimal solutions rather than local optima (Derhami et al., 2020).

The range of performances in the Pareto frontiers increases with problem size moderately. The total variation in waste between the extreme frontier points (50% waste at high-utilization and 70% waste at travel-optimized) in a small warehouse is between 15 and 20% points, and in a large warehouse is between 25 and 30% points (Derhami et al., 2020). The increased assortment indicates more design freedom in large plants where dimensional freedom allows a wider variety of designs. The number of vehicles decreased between high-utilization and travel-optimized designs is found to be relatively constant at 18- 22% in the problem scales, indicating that the cross-aisle advantages increase in proportion to the size of the warehouse (Chen et al., 2011). The systematic improvement of proportions is important to show that optimization value is significant despite the size of the facility, and systematic layout designing is justified to small and large warehouses, although solving larger problems is more complex.

D. Comparative Analysis with Alternative Storage Location Assignment Policies

➤ *Reference Model Performance Under Random within-Class Assignment*

To measure the extent of performance improvements due to the improved class-based storage policy that incorporates closest open location assignment, comparative analysis was done with a reference model that adopted the traditional class-based policy where assignment is done randomly within classes. The reference model has the same definition of classes and zone boundaries but randomly designates incoming inventory to any available position in the specified and designated class zone instead of the lowest-distance position (Muppani and Adil, 2008). The incremental worth of the tactical closest-open-location selection is set off in this comparison with the strategic class-based framework, as the benefits obtained due to class-based zoning versus those obtained with within-zone assignment optimization are isolated (Kovács, 2011).

Reference model using random within-class assignment has a space utilization of 52.31% (47.69) waste, which is the same as the enhanced policy since both policies make use of the same storage capacity. The decisions to use space rely mainly on the decisions of the size of class zones and capacity allocation that are not affected by the policies (Derhami et al., 2020). The physical location of physical inventory in zones is influenced by the assignment rule (random or closest-open) and not by the overall zone occupancy rates, which is why the utilization metrics are the same. This equivalence proves that the benefits of the improved policy are operational efficiency effects and not capacity effects and that travel distance is the main performance dimension that is influenced by assignment refinement (Quintanilla et al., 2015).

Nevertheless, the number of vehicles demanded would rise to 42.88 equivalent full-time forklifts in the case of random assignment, which is a 24.5% growth in the material handling capacity demands. This huge disparity is caused by the fact that the average travel distances are longer in the case of the random distribution of inventory across class zones

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instead of concentrated in the most optimal positions (Derhami et al., 2020). Random assignment sometimes places commonly-used items at the far extremes of specified areas, and thus causes the maximum distance between input/output points even when a favourable zone selection is made. By contrast, closest-open-location minimizes individual assignment distances in a systematic way with the concentration of inventory around to zone boundaries around pickup and delivery zones (Muppani and Adil, 2008). The summed-up impact of thousands of daily operations translates to the realized increase in vehicle requirements as more distance is covered by the equipment during standard replenishment and retrieve routines.

The mean travel distance per operation rises by 23.5% in enhanced policy to random assignment 238 feet to 294 feet. In detail, it is possible to note that the difference is concentrated in certain types of movements (Derhami et al., 2020). The distances between production and storage grow by 31% (between 168 and 220 feet on average) during random assignment (production to storage) when the incoming inventory is occasionally placed in the far sites even though there are vacancies nearer. The distance of storage-to-dock retrieval increases by 18% (from 275 to 325 feet) when accumulated random assignments result in dispersed inventory distributions that retrieval processes need to contend with. There are also no significant changes in vehicle-to-parking distances (they only increase 4-fold) because the parking location is immobile and the assignment policy has no impact on empty vehicle flows (Quintanilla et al., 2015). The relative effects of the various types of movement suggest that the assignment policy has the greatest influence on the loaded travel distances in which inventory placement is important and the empty repositioning movements are less responsive.

Economic analysis shows that random within-class assignment is subjected to extra expenses in the form of approximately 633, 000 annuals over and above the improved policy ($75,000 per vehicle × 8.45 additional vehicles). This price loss proves the high degree of practical utility of the integrations of closest open location logic into frameworks of classes (Muppani and Adil, 2008). Companies engaging in the concept of class-based storage that lacks distance-based assignment optimization lose a significant degree of operational effectiveness even though they manage to obtain desirable strategic placement using turnover-based zoning. The cost of equipment increase of 633,000 is a material cost of 14.4% of the overall operational expenditure of the warehouse, which should generate the interest of cost-sensitive managers (Derhami et al., 2020). Close-open-location logic implementation necessitates only slight improvements to the warehouse management system (estimated cost of $15,000-25,000 to make changes in the software and test) that will be recovered within 2-3 weeks of operation, which is a significant payback (Kovács, 2011).

➢ *Performance Comparison with Dedicated and Pure Closest Open Location Policies*

The results of simulation of the beverage warehouse with dedicated storage policy indicate that the space utilization is 38.2% (61.8% waste), which is significantly less than 56.8% obtained using class-based methods. The utilization penalty is due to the capacity that is allocated to low- turnover products which do not occupy their designated space on a regular basis (Derhami et al., 2020). The products with seasonal demand pattern or promotional upsurge demand space to stock the peak inventories, which would remain unused during low seasonal periods when inventories would be left at the minimum levels. The waste gets piled up in many low-turnover SKUs, which add minimal amounts of reserved-but-unused capacity that cumulatively reduce the overall utilization (Kovács, 2011). high-turnover products keep their allocated locations always full, yet the good behaviour cannot compensate the aggregate wastage of more slowly-moving products. The 38.2% utilization is the median case among twelve simulations; worst-case scenarios in seasonal troughs have utilization as low as 31% whilst peak-season periods have a maximum of 44% which shows great temporal fluctuations inherent in dedicated policies (Xiao & Zheng, 2010).

Nevertheless, dedicated storage has good performance in travelling distance with necessary vehicle level of 36.1, between improved class based (34.4) and random class based (42.9) policy. This average performance represents scaled-down fixed assignments with favourable positions of high-turnover products but with the lack of the dynamism of close open location methods (Muppani and Adil, 2008). The committed tasks can be optimized with the early warehouse arrangement with historical data to locate the regularly-utilized SKUs close to input/output spots, practically introducing a lasting class-based design. Nonetheless, the fixed assignments are unable to react to the shifting demand pattern, variation in inventory make-up, or operational disturbances that change optimum placement in the long run (Derhami et al., 2020). Products whose demands grow are left in their originally-allocated locations although close substitutes can be found whereas those whose demand is falling maintain superior positions that could be used more effectively by other products. The inability to change long-term results restricts the performance in the long run because the situation in the warehouse changes, but the short-term results immediately after optimization can be close to the results of the classes (Kovács, 2011).

In pure closest open location policy, all incoming inventory is allocated to the closest available location irrespective of the nature of the product without zoning by classes. This model has a high degree of space usage of 57.2, which is almost equal to the policies of classes since no space is allocated and no area is limited (Derhami et al., 2020). All incoming products may be placed in any available storage position, which maximizes the flexibility and removes specific wastes. The policy inherently focuses inventory around input points whereby the incoming shipments are first stored at levels closest to goods first, thus forming a positive cluster positioning around goods that just arrived (Quintanilla et al., 2015). This concentration is however short lived as outbound shipment drains off around positions leaving vacancies filled by the arrival of other ships. The high rate of

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turnover slowly spreads inventory across the facility, blurring the positioning edge first attained.

Travel distance performance is intermediate with the needed vehicle count 39.3, between dedicated (36.1) performance and random class-based (42.9) performance. Although closest open location is expected to keep inventory close to the input points at first, over time, products will eventually be distributed across the entire facility, and the positioning advantage will be diluted (Derhami et al., 2020). Products with high turnover spend a short period of time in storage taking up near positions and leaving after a short time. In the meantime, sluggish products are stored temporarily on busy territories (wherever they were placed when they arrived) and may spend long durations of time in the near-dock area, with speedy movers being held out in remote areas (Muppani and Adil, 2008). The policy does not provide strategic locating of high-turnover products, which means that items with high frequency of access can be relocated to other areas depending only on the availability of storage at the time of arrival. This stochastic time movement worsens the performance of travel distance as opposed to strategic positioning of classes that ensures fast-movers are always in shipping regions (Kovács, 2011).

Table 5 Comparative Performance of Storage Assignment Policies

Assignment Policy	Space Utilization (%)	Waste (%)	Vehicles	Avg Distance (ft)	Annual Vehicle Cost ($K)	Policy Complexity	Implementation Cost ($K)
Dedicated Storage	38.2	61.8	36.1	264	2,708	Low	5-10
Random Storage	58.1	41.9	44.2	312	3,315	Very Low	2-5
Closest Open Location	57.2	42.8	39.3	283	2,948	Medium	15-25
Class-Based Random	56.8	43.2	42.9	294	3,218	Medium	15-25
Enhanced Class-Based	**56.8**	**43.2**	**34.4**	**238**	**2,580**	**Medium-High**	**25-35**
Hybrid (Class + Dedicated)	44.3	55.7	35.8	259	2,685	High	35-50

Table 5 shows a detailed performance comparison report of six policies of storage location assignment with the same warehouse layout and operational conditions. The table reports the percentage of space utilization, the percentage of waste, the number of vehicles that should be required of each operation, the annual vehicle-based costs of $75,000 per vehicle, the subjective rating of policy complexity, and the estimated implementation costs (Derhami et al., 2020). The improved policy of classes based on nearest open location choice in zones produces the lower vehicle requirements (34.4) and travel distances (238 feet) and favourable space utilization (56.8%), which produces minimum annual vehicle costs of 2580K. Dedicated storage offers the least space utilization (38.2%), but has moderate travel distance (264 feet, 36.1 vehicles) in exchange of consistency and efficiency. Random storage offers the greatest simplicity but creates the greatest vehicle needs (44.2) and maximum vehicle distance (312 feet), at an annual cost of 3315K, which is 28.5% more than the improved policy (Muppani and Adil, 2008). Pure closest open location has an intermediate performance (39.3 vehicles, 283 feet) and an excellent space utilization (57.2%), which can be used as a possible alternative to operate in the case of operations where a focus on simplicity is preferred over optimization. Class-based random assignment does worse than the improved one by 24.7% on vehicle demands (42.9 versus 34.4) with the same amount of space used, where the distance within a zone is optimized. The hybrid policy that unites class-based zoning with dedicated assignments within classes provides slight increases over dedicated policies but it cannot match the totally dynamic policies (Zhou et al., 2016).

Comprehensive comparative evaluation supports the result and proves that an improved performance offered by the improved class-based policy with the nearest location assignment on the territory of the zones is better, its performance will be characterized by high space utilization (56.8%) and low travel distances (34.4 vehicles). This combined method combines advantages of a strategic approach that is class-based positioning with tactical closest open location assignment, without limitations of pure approaches (Derhami et al., 2020). The policy has some effective benefits such as it can be easily implemented in most warehouse management systems only defining classes, zone boundaries, and distance calculation features, which are common in most of today WMS platform (Xiao and Zheng, 2010). Natural adaptation As changing demand patterns occur the closest-open-location logic will automatically adjust to those changes without the need to be manually adjusted or reoptimized on a periodic basis. The agility is very responsive as opposed to steadfast policies where reassignments occur periodically as the demand requirements vary drastically (Kovács, 2011).

E. Operational Insights and Design Principles

➢ *Impact of Cross-Aisle Additions on Travel Distance and Space Efficiency*

Pareto frontier solutions can be studied systematically to obtain some basic relations between the number of cross-aisles and performance indicators in different warehouse systems. The distance reduces significantly with the increase

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in the number of cross-aisles (2 vs. 6) with a reduction of 15-25% across the dimensions of the warehouses and SKU mix (Derhami et al., 2020). The first advantage is the worth of developing orthogonal aisles that allow one to move straight across the aisle instead of having to move equipment around the premises. The cars moving between aisle spaced by the width of the warehouse would have to go all the way across the length of the warehouse to access perimeter aisles and the width all the way back to the destination aisle, a very meandering path (Pohl et al., 2009). The initial addition of cross aisles penetrates this long route, and offers a short cut, which cuts inter aisle movement distances by 20-30%. The additional cross-aisles at 2-6 counts proceed to deliver significant routing advantage of saturating shortcut accessibility and minimal distances to nearest cross-aisles.

The 2-6 range offers considerable shortcuts of route with each extra cross-aisle, minimizing the paths through the movement of an average operation. The analysis of movement shows that rates of cross-aisle use (percentage of trips using at least one cross-aisle) rise to 32% with 2 cross-aisles available to 78% with 6 cross-aisles available, which proves the growing routing dependency on the cross-aisles (Derhami et al., 2020). The savings of the distance per cross-aisle use is 85 feet which is a significant saving of efficiency. The operators of equipment soon become familiar with the best routing patterns, preferential routing being taken along with cross-aisles where possible (Roodbergen & Vis, 2009). The behavioral adaptation enhances the benefits of cross-aisle with the effects exceeding pure geometric analysis since experienced operators use routing choices more efficiently than naive short-path algorithms presuppose.

Nevertheless, at cross-aisles 6-8 marginal improvements go down on a steep slope. The increase in cross-axis 9-12 only gives a cumulative benefit of 4-6, and additional additions do not have significant measurable benefit (Derhami et al., 2020). The diminishing returns phenomenon takes place since too many crossing aisles constitute unnecessary routes that add little routing benefit. After achieving a 8-10 lane interval between cross aisles, most movements is served by relatively direct courses, and tightening the spacing does not give much additional value (Pohl et al., 2009). The closest cross-aisle to any storage site is on the average of 4-5 lanes with 8 cross-aisles hence routing distances are brought down to almost optimal distances. Additional cross-aisle extensions, although minimally affect this average distance (to 3-4 lanes having 16 cross-aisles) with proportionately less benefit. Moreover, cross-aisle travel time partially negates the routing benefits since each cross-aisle travel takes 12-15 seconds (average) and cross-aisle movements involving more than one cross-aisle incurs delays (Derhami et al., 2020).

The high density of cross-aisle networks can augment some movement traveling distances of those movements that have to pass through several cross-aisles before routing. In 16+ cross-aisle layout designs, equipment moving between near-dock storage points to far-dock shipping locations occasionally crosses three or more cross-aisles, adding 36-45 seconds of cross-aisle travel time (Derhami et al., 2020). By contrast, the identical movement in layouts with 4-6 cross-aisles is usually made by a single cross-aisle, and accruing 12-15 seconds of cross aisle time, but possibly traversing slightly further primary aisle distances. The overall consequence usually supports moderate cross-aisle counts (6-10) over extreme densities (16+) relative to pattern of movement, but overall benefits of all types of movement patterns are observed towards higher cross-aisle counts to around 12-14 (Chen et al., 2011).

The percentage of space wasted grows in direct proportion to the number of cross-aisles since each extra cross-aisle will take up equal proportional floor space on access infrastructure as opposed to storage. In case of regular warehouse sizes and unidirectional cross-aisle widths, adding an additional cross-aisle raises the percentage of wastes by around 1.5-2.0% points (Derhami et al., 2020). The direct geometric effect of consumption of the cross-aisle space is the linear relationship between cross aisle area and the length of the warehouse cross aisle and width, which does not change with an increase in the number of cross aisles. Total cross-aisle area is a linear accumulation with count. In the case of the beverage warehouse, cross-aisles consume 3,600 square feet (368 feet length 9.8 feet width) which is 0.98 of the total facility area of 368,000 square feet (Fernando et al., 2021). The facility has 16 cross-aisles with a dedication of 57,600 square feet or 15.7 per cent facility area which can hold 2,400 pallet positions based on stacking heights.

The trade off between reducing the distance returned on the travel and increasing the waste of linear space, creates a range of optimal cross-aisle counts, which are 4-8 cross-aisle counts in a medium to large warehouse, and any further added cross-aisle counts is associated with net performance penalties when the two objectives are equally weighted (Derhami et al., 2020). However, cost-based optimization tends to prefer more cross-aisles (10-16) when the material handling costs (are much higher) than the space costs because savings in the travel distance are more economically valuable than penalties in space wastage in handling-cost-dominated situations. Ideal number thus being dependent on cost parameter ratios and is of critical importance with $\rho = c_v/(c_s \cdot A_{\text{total}}) > 0.35$typically favoring 12-16 cross-aisles while $\rho < 0.20$favors 4-6 cross-aisles (Accorsi et al., 2014). Organizations should determine optimal cross-aisle counts based on organization-specific economics rather than generic rules of thumb, as economic contexts vary widely across industries and geographic regions.

➢ *Aisle Configuration Effects and Bay Depth Optimization Principles*

Analysis of optimal aisle counts across diverse problem sizes validates the analytical model $n_a^* = \sqrt{\frac{S_l N_s}{4 S_w A}}$as a sound indicator of space-efficient settings. The observed optimal aisle counts in Pareto frontier solution are clustering well around analytically-predicted value, typically within +/-1 aisle in problems to 300 SKUs and within +/-2 aisles in problems only somewhat larger (Derhami et al., 2020). This consistency is a testament that waste minimization framework is a representation of underlying space utilization trade-offs that control the relationship between aisle-bays depth. The two competing waste sources balanced in the analytical model are waste of accessibility of aisles themselves (proportional to aisle count n_a) and geometric/honeycombing waste from bay structures (inversely proportional to $n_a$through bay depth effects) (Le-Duc & de Koster, 2005). The optimal balance occurs at $n_a^*$where marginal waste increases from adding another aisle exactly equal marginal waste decreases from enabling deeper bays, creating an equilibrium that generalizes across diverse warehouse configurations.

The close relations between the predictions of the analytical model and optimal solutions obtained through simulation with the help of the simulation confirm some of the main assumptions that the analytical model occurs to be based on. The model presupposes that all storage areas have equal bay depths, that the characteristics of the products in a collection are homogeneous, and that the dynamics of the inventory is steady-state, which are simplifications that may be likely to restrict precision (Derhami et al., 2020). Nevertheless, these abstractions have been empirically proven to preserve vital relationships as well as allowing solvable closed-form solutions. The reason behind the accuracy of the model lies in its emphasis on aggregate volumetric waste other than detailed operational dynamics to represent first-order effects, which prevail in space usage, and second-order variations, which become averaged out by high-facility size and product portfolio diversification (Heragu et al., 2006). This observation implies that simple analytical models easily inform planar layout choice (number of aisles, bay depth), whereas tactical choices (location of individual aisles, cross-aisle locations) entail more advanced computational optimization.

Increasing aisle numbers beyond n_a^*reduces space utilization monotonically due to additional accessibility waste from proliferating aisles. However, travel distance improvements are modest and inconsistent (Derhami et al., 2020). Layouts with $n_a = n_a^* + 2$typically achieve 3-5% travel distance reductions compared to $n_a = n_a^*$configurations, while suffering 8-12% space utilization penalties. The asymmetric trade-off also renders the large number of aisles economically undesirable unless in special applications where $\rho > 0.50$(Chen et al., 2011). Even where such cases arise, cross-aisle additions usually give better travel distance improvements per unit space lost than do additional aisles, and the choice of cross-aisles is the most favored way of improving travel efficiency. The above-mentioned additional aisles are beneficial to the modest travel due to being of parallel orientation, increasing the number of access points to the storage without fundamentally reducing the routing paths between input/output locations and storage sites (Pohl et al., 2009).

Conversely, reducing aisle counts below n_a^*degrades both objectives simultaneously—space utilization declines due to increased honeycombing in excessively deep bays while travel distances increase as equipment traverses deeper into storage lanes (Derhami et al., 2020). Bays deeper than optimal ($\bar{x} > \bar{x}^*$) experience two effects: first, geometric waste is aggravated by rear lane positions taking up proportionately more volume as access space compared to storage positions; and second, there is enhanced honeycombing waste as deep bays take longer to fill and empty and extend periods of time during which a lane is partially occupied (Le-Duc and de Koster, 2005). Penalties on travel distance also accrue, as the average distance into storage bays rises in direct proportion to the depth of those bays-20-pallet-deep storage bays have an average distance of 10 pallets to aisles, 15-pallet-deep storage bays have an average distance of 7.5 pallets to aisles, a 33% distance increase. This is because these two fines result in sub-optimal aisle counts (below n_a^*) universally inferior across all cost parameter ranges, confirming that n_a^*represents a firm lower bound for practical design (Derhami et al., 2020).

These observations establish practical design guidelines that warehouse planners can apply with confidence: first, configure aisle counts near analytical predictions n_a^*, recognizing this provides space-efficient foundations; second, use cross-aisle additions to achieve travel distance improvements rather than excessive aisle proliferation, as cross-aisles offer superior efficiency per unit space consumed; third, recognize that space-efficient solutions ($n_a \approx n_a^*$) give it preferential entry points that can be optimised under specific cross-aisle positioning according to the economic factor (Derhami et al., 2020). The decreasing marginal returns to additional aisles contrasts with the high initial returns to strategic cross aisle additions, indicating that design work should focus on cross-aisle optimization when the basic aisle configuration methods find analytical optimum. The priority is used in resource allocation in warehouse design projects, where analytical attention and computational effort is directed towards the high-impact design variables (cross-aisles) more than the lower-impact factors (excessive aisle variations beyond n_a^*) (Kachitvichyanukul & Sooksaksun, 2012).

➢ *Input/Output Point Positioning and Facility Geometry Considerations*

Sensitivity analysis on the location of input/output points indicates significant performance changes especially in warehouses whose length to width ratios are high. Plants with length significantly large relative to width (aspect ratios greater than 2:1) generate long storage spaces in which the layout of production lines, receiving docks, and shipping spaces has a fundamental impact on travel distances (Derhami et al., 2020). The case study of the beverage warehouse also has a moderate sensitivity to the I/O positioning with an aspect ratio of 1.84:1. Comparisons that were made experimentally compared I/O configurations but with the same aisle and cross-aisle layouts, eliminating geometrical effects of layout structure (Heragu et al., 2006).

Setups placed at the short sides of rectangular warehouses (perpendicular to the storage lane orientation) are always very successful compared to those that place I/O points on long sides. In warehouses having length-to-width ratios of 3:1, short-side I/O placement is 18-25% lower than long-side placement in terms of travel distances (Derhami et al., 2020). This benefit can be attributed to geometric relationships that lanes running along short sides establish relatively constant distances between I/O points across the width of the warehouse with the greatest difference in distance of no more than 1.5x between nearest and far-reaching aisles. By comparison, long-side I/O placement produces very large distances between near and far edges (3-4x) with extreme distance distributions (Pohl et al., 2009). The beverage warehouse whose I/O is on long sides has the highest distance of 368 feet between opposite end docks and storage points and hypothetical positioning of the short ends would have a maximum distance of 200 feet - an 84% reduction in maximum traveling requirements.

Cantered I/O position based on the facility edge give small benefits over corner positioning, decreasing the mean distances by 5-8% by means of better spatial balance (Derhami et al., 2020). Corner I/O placements generate an asymmetric distance distribution that is heavily biased towards distant store points, and 60-70% of the locations have distances above the average. Cantered position is applied to give more balanced distributions where 45-50% of positions fall above averages and less variability and extreme distances (Roodbergen & Vis, 2009). The enhancement is most pronounced in large-facilities at which corner-to-opposite-corner distances are 400+ feet--cantering I/O will cut the maximum distances by 100-150 feet in these extreme motions. Nonetheless, cantered positioning demands dock placements in the middle of the facility that might be incompatible with the structural layout, material movement patterns or truck manoeuvring space, restricting it to an actual facility that has a fixed perimeter dock layout (Chen et al., 2011).

I/O point configurations of dual I/O points with production/receiving on one side and shipping on the other save between 12-15% travel distance over single side I/O point configurations, especially when paired with strategic cross-aisle spacing between I/O areas (Derhami et al., 2020). The dual setup allows the equal flow of materials where the incoming inventory flows into one side and through the storage and flows into the other side -forming directional flows that minimize back tracking and empty travels. Close cross-aisles located on either side of the I/O sides ensure an effective way to reach the storage spaces using the docks whereas the transfers between the zones are made using the middle cross-aisles (Pohl et al., 2009). The warehouse is now using dual-side I/O with production docks on the west long side and shipping docks on the east long side and is performing better than single-side alternatives but poorly in comparison with hypothetical short-side configurations that cannot be geometrically constrained.

These results indicate that warehouse design is to take I/O point positioning as the part of the holistic optimization of the layout instead of the limitation imposed on it (Derhami et al., 2020). The new warehouse constructions project must focus on I/O positioning decisions during the early stages of the design with orientation of facilities to allow short side docking where land layouts allow. The aspect ratios that are less than 2:1 are operationally advantageous over I/O benefits such as equal or nearly equal travel distances, symmetrical material flows, and geometric flexibility to expand in future (Heragu et al., 2006). When layout design is required to accommodate known I/O positions in existing facilities where the facilities are structured to predetermine aisle orientations and cross-aisle locations, the layout design should adjust aisle orientations and cross-aisle locations to suit fixed I/O locations in the best way possible. Where possible, lanes must be perpendicular to I/O-bearing sides and cross-aisle networks are expected to allow direct routing between I/O points and high-density storage areas (Derhami et al., 2020). In situations where the facility can be adjusted, it may be cost-effective to move I/O points to geometrical locations that favour reduced travel distances, potentially leading to cost savings much larger than the investments made in infrastructure (especially in large facilities with large volumes of operations) where the savings on travel distance will add up to a large annual saving of over $200,000-500,000 (Accorsi et al., 2014).

IV. DISCUSSION AND CONCLUSIONS

A. Research Contributions and Theoretical Implications

- *Integration of Layout Design with Storage Assignment Optimization*

The study contributes to the theory of warehouse design due to the creation of a single optimization model that considers both the policy of spatial layout arrangement and the policy of operational storage assignment. Past studies largely considered these areas of decisions separately and either optimized layout under the assumption of generic storage policies or optimized assignment under the assumption of fixed layouts (Van Gils et al., 2018). The sequential strategy generates suboptimality since layout features essentially determine the effectiveness of storage assignment, whereas assignment policy determines the way layout features are converted into working performance. The integrated strategy considers the following interdependencies: layout structure defines accessible storage locations, pathway networks, and distance relations, and assignment policies define how locations are used, accessed, and occupied across different periods of time (Derhami et al., 2020). Simultaneous optimization finds better coordinated solutions that cannot be found by sequential methods which optimize a decision level and fix another.

The model shows that the policies relating to storage assignment have a strong interaction with the layout properties and produce various performance profiles at alternate designations. Random within-class assignment can be done in a compact layout reasonably well (small warehouses with 200-400 feet dimensions) but with a large penalty in a large layout (where random positioning can put items 300+ feet off optimum locations) (Muppani and Adil, 2008). The decrease in performance with the size of the warehouse- 10% penalty in small warehouses and 25% penalty in large warehouses are then compounded by the fact that absolute positioning errors are directly proportional to the amount of space available. On the other hand, closest open location assignment is uniformly advantageous on various layouts, and greater absolute gains on large facilities where tactical positioning choices influence movement at longer ranges (Quintanilla et al., 2015). These interactions confirm that the optimization of layout must be modelled to directly consider desired policies of operation instead of making assumptions about generic assignment behavior that might not be indicative of actual practice.

Theoretically, the integrated approach extends the field of study of warehouse design to go beyond spatial optimization and into more of a system design, including physical infrastructure and operational logic (Derhami et al., 2020). This holistic perspective goes hand in hand with general trends in the logistics systems engineering that have appreciated that the best system performance is achieved through coordinated entities of multiple decision layers as opposed to unsynchronized optimization of the different components. The methodology gives a template that can be used in other warehouse design challenges with coupled spatial and operational choices, e.g., zone design that is synchronized with order batching policies, or slotting optimization that is synchronized with picker picks strategies (Van Gils et al., 2018). The broad concept, that physical design and operational policy should be optimized together as opposed to sequentially is not only relevant to the warehousing but also to the manufacturing systems, distribution networks, and service operations where the infrastructure and operational decision-making interact in a complex way.

➢ *Analytical Foundations for Computational Optimization*

The development of closed-form analytical solutions for optimal aisle numbers provides valuable theoretical contributions beyond their immediate practical utility. The model $n_a^* = \sqrt{\frac{S_l N_s}{4 S_w A}}$represents the first analytical treatment explicitly maximizes the total warehouse waste and does not the block configurations separately (Derhami et al., 2020). The analytical models developed in the past such as the seminal lane depth formulation of earlier researchers aimed at optimization of the use of space in individual storage blocks characterized by fixed positions of the aisles (Le-Duc & de Koster, 2005). These block-level models do give local optimization advice, but are not able to compute system-level aisle counts in a trade-off of the competing needs of multiple blocks. Whole-warehouse view considers the trade-offs in aisles throughout the entire facility in that an ideal combination in aisles minimizes accessibility waste and at the same time honeycombing and geometric waste in bay structures (Derhami et al., 2020).

The high empirical validation of the analytical model in the context of various problem scope proves that there exist general space utilization principles that go beyond the warehouse conditions. The model can predict the optimal aisle counts of facilities of all sizes and with all three types storing 10 to 1,000 SKUs at a consistent average of 0.3 aisles deviation between the model and the simulation-derived optima (Derhami et al., 2020). Such a generalizability implies that the hidden waste minimization structure represents a captivity of fundamental physical and operational phenomena that control space efficiency in a manner independent of scale, product mix, or demand patterns. The mathematical ease of the model, with only warehouse dimensions, SKU number and aisle width, contributes to the practical feasibility, with quick preliminary design evaluations that are not computationally optimized (Heragu et al., 2006). Planners in the warehouse can calculation n_a^*within seconds using basic calculators, providing immediate guidance during early design phases before detailed simulation studies commence.

The computational optimization model also offers strict foundations based on computational optimization, setting theoretically-justified boundaries of search space allowing to avoid wasting efforts in the evaluation of configurations that are evidently suboptimal (Derhami et al., 2020). Instead of using random parameter ranges (e.g. random sampling of aisle counts, 1 to 30 based on dimensional feasibility alone) or exhaustive enumeration and exploration the whole of that space with high probability of including optimal solution, the framework predicts exploration space analytically (high probability of including optimal solution in that space). Theoretically-based definition of search space is much more efficient computationally, cutting the number of scenarios by 60%, but ensures those that are actually optimal are not missed by mistake (Kachitvichyanukul and Sooksaksun, 2012). The methodology can be viewed as a good example of successful incorporation of analytical and computational approaches, where respective advantages (analytical: quick assessment, conceptual understanding; computational: complexity, stochasticity) are used to address limitations of single methodologies.

The convexity proof for the waste minimization function confirms that n_a^*represents a global optimum rather than local optimum, providing theoretical guarantee of solution quality (Derhami et al., 2020). The second derivative $\frac{d^2 f}{d n_a^2} = \frac{S_h N_s S_l}{2 n_a^3} > 0$for all positive parameter values establishes strict convexity, ensuring no local minima exist that could trap optimization algorithms. This theoretical property justifies using simple derivative-based solution methods rather than requiring sophisticated global optimization algorithms, simplifying both analytical derivation and computational implementation (Balakrishnan et al., 2003). The convexity also provides insights into sensitivity characteristics—the function exhibits steeper curvature near optimal values, meaning that small deviations from n_a^*create disproportionate performance penalties, while larger deviations in already-suboptimal regions create relatively smaller incremental penalties.

➢ *Multi-Objective Optimization Framework for Conflicting Design Objectives*

The cognitive expression of warehouse design as an optimization problem involving the use of Pareto frontiers to characterize the multi-objective problem enhances theoretical knowledge and utility in making decisions. Past studies tended to condense several goals into one-objective models using priority hierarchies or weighted sums, which inherently imposed certain preference structures, which in turn might not be realistic organizational priorities (Accenture, 2008). As an example, formulae minimizing $\alpha \cdot W + \beta \cdot N_v$where $\alpha$and

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β represent weight parameters assume that decision-makers can make relative valuations of space waste and vehicle requirements prior to solution space exploration. It is a problematic method in the situations when the relative valuation is unpredictable, context-specific, or disputed by the stakeholders (Balakrishnan et al., 2003). Pareto frontier methodology maintains the entire spectrum of the trade-offs so that decision-makers may opt to choose solutions according to organization specific cost structures and strategic priorities once they have seen the visual display of available options instead of making the weight parameter decisions too soon.

The study shows that the use of space and minimization of the distance of travel generate true trade-off relationships and do not strengthen synergies, which is contrary to the intuitions according to which increasing efficiency in one dimension is bound to positively influence other dimensions (Derhami et al., 2020). Space-maximizing layouts have 20-30% greater material handling capacity than space-minimizing layouts, and travel-minimizing layouts have 30-40% lower space efficiency than space-maximizing layouts. The high level of this trade-off, 20-40% point differences, and not 2-5% differences as might be expected of a surrogate relationship between the objectives but rather optimization of one allegedly optimizes the rest supports the critical need to explicitly treat each of the objectives in a multi-objective process (Heragu et al., 2006). The high negative correlation of space utilization and travel efficiency (r = -0.89) among Pareto solutions proves that these two goals are at variance with each other and a balance should be exercised instead of win-win solutions that are both more goals of maximization of both dimensions.

Identifying the optimal outcomes according to the Pareto frontier description, the most promising solutions were clumped into specific sets of design philosophy: the dense storage with little infrastructure and distributed storage with large pathways network (Pohl et al., 2009). This clustering offers strategic information that hints that middle-way compromises can be not as good as making a definite commitment to either the space-efficiency or the travel-efficiency priorities. The cost analysis of frontier solutions reveals that moderate levels (intermediate numbers of cross-aisles 6-8) seldom attain the minimum costs within very narrow ranges of the ratios of cost parameters around 0.25(Derhami et al., 2020). The majority of cost situations are biased towards the high-utilization designs ($n_c = 2 - 4$) when $\rho < 0.20$or travel-optimized designs ($n_c = 12 - 16$) when $\rho > 0.30$, and a comparatively limited number of situations in which the middle ground is appropriate. This observation indicates that decision-makers who are faced with uncertain cost structures must look at selecting solutions in frontier endpoint or near-endpoint regions instead of middle positions because these structures have strong performance in the face of parameter uncertainty (Heragu et al., 2006).

The study also displays methodological improvements in the Pareto frontier construction of the simulation-based optimization problems in which the objective functions evaluation is realized by costly stochastic simulation (Derhami et al., 2020). The pre-simulation assessment phase does deterministic distance computations to rule out solutions that are obviously dominated prior to the costlier simulation, which reduces the computational load by some 45% and retaining all truly non-dominated ones (Zhang and Li, 2024). The filtering takes advantage of the fact that layouts in which the space allocated to cross-aisles is the same but the overall distances are worse than those of a layout in the Pareto frontier must occur in the Pareto frontier despite the stochastic operational characteristics. Deterministic screening also finds solutions which are dominated in a sure way as compared to sampling which may not be sure in classification of solutions because of statistical noise in the performance estimates (Caron et al., 2000). The contribution in terms of methodology extends to other multi-objective optimization problems involving simulations where the partial ordering of the problem characteristics by deterministic data is possible to remove dominated alternatives before stochastic evaluation can be completed.

B. Practical Implications and Implementation Guidance

➢ *Decision Framework for Layout Selection Based on Cost Structures*

The study offers systematic designs to warehouse managers and logistics planners on how they can choose the right layouts depending on the economic situations of the organization. The cost ratio $\rho = c_v/(c_s \cdot A_{\text{total}})$is a single dimensionless parameter that assesses relative significance of material handling and space costs, and it is fast to evaluate what Pareto frontier area is likely to have optimal solutions (Derhami et al., 2020). Organizations can calculate ρ based on easily obtainable financial data, including equipment expenses, labor charges, facility lease, or ownership expenses, and refer to frontier solutions in the right ratio range. An example is a warehouse that incurs an annual vehicle cost of 75,000, facility space cost of 0.85 per square foot, and area size of 368,000 square feet, which gives a calculation of 0.024, that is, low relative emphasis on handling costs (Accorsi et al., 2014). This small ratio however may still create dominance of handling-cost in total magnitude when large numbers of vehicles are needed because absolute handling-costs ($75,000 × 35 = $2.625M) are significantly higher than space waste-costs (8.50 × 368,000 × 0.43 = $1.343M).

In organizations whose 0.15 (space-cost-dominant environment like urban warehouses with high real estate prices) 0.15 defines the strategic planning of space, the optimal layouts would focus on the use of space by minimizing cross-aisles (2-4) and aisles close to analytical estimates n_a^*(Derhami et al., 2020). These configurations are usually able to be operated to 55-60% utilization and need 15-20% more material handling capacity than travel-optimized versions. The space savings are translated into such tangible benefits as deferred facility expansion investments (which may save 5-10M in construction costs), decreased lease payments by third-party logistics providers (which can save 300K-500K per year), or available capacity that facilitates higher inventory levels that can support improved service

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levels (Manzin et al., 2015). Companies located in Manhattan, San Francisco, London, or other luxury real estate areas have space expenses of 25-50/ft In/year, which generates values of poorly less than 0.15 even using expensive equipment and personnel. Such settings clearly prefer space-efficient designs even in the face of cost escalations.

Intermediate ratios 0.15repture 0.35(balanced cost structures): the ideal solution is with moderate proportions of cross aisles (6-10) with 45-50% utilization with almost the minimum travel distances (Derhami et al., 2020). Such configurations strike a balance between conflicting goals without sacrificing one at the expense of the other without compromising performance on either of these two dimensions to satisfactory levels. The intermediate regime typifies most of the industrial warehouse in suburban areas where moderate land prices (8-15 per square foot) offset high labor prices (60K-90K per worker) and equipment prices (50K-100K per vehicle) which form the real trade-off decisions and will require thorough analysis (Heragu et al., 2006). Companies under this regime are advised to do sensitivity analysis of performance over possible range of cost parameters, analysing the strength of solutions by the candidates to economic uncertainty. Plans that are close to optimum with changes in cost parameters by 20-30% give safer choices compared to highly specialized plans which are only optimum with very limited assumptions.

In 0.35(handling-cost-dominant) case (suburban warehouses with intensive labor activities), the travel optimal layouts with large cross-aisle networks (12-16) help in minimizing vehicle requirements even under low utilization (Derhami et al., 2020). These settings produce significant savings of equipment fleets in a year.

(Saving $300K - 600Kannuallyinvehicle - relatedcosts)andimprovedthroughputcapacity(enabling15 -$ 20falls squarely in this regime, explaining optimal selection of Layout 9 with 16 cross-aisles despite 65% waste.

In addition to quantitative analysis of the cost, qualitative considerations play a role in layout choice in practice. Considerations of implementation feasibility are disruption to transition (layouts that need few or no changes to current structures minimize downtime, and one-time costs), familiarity among the operators (structural layouts that look similar to existing layouts are easy to train and also reduce transition errors), future changeability (layouts that allow capacity expansions or changes in product mix can be changed without incurring significant redesign costs), and physical constraints (structural columns and loading docks, building codes can constrain feasible layouts irrespective of the optimization outcomes) (Derhami et al., 20 These considerations at times supersede pure cost optimization and organizations will use a layout that is a bit suboptimal (within 5-10% of minimum cost) and has better implementability, flexibility or fit with long-term strategic plans. These subtle decisions are supported by the Pareto frontier presentation which shows various near-optimal options that allow one to consider other secondary criteria than the primary cost goals (Balakrishnan et al., 2003).

➢ *Implementation Strategies and Transition Planning*

The process of changing current layouts to optimized layouts ought to be carefully planned regarding operational disruption, the cost of transitioning, as well as change management. The implementation of the case study demonstrates realistic strategies that can be applied in the context of organizations (Derhami et al., 2020). The first step made by the organization was the comprehensive simulation of the optimized layout to verify performance forecasts and possible implementation issues to determine how much resources should be devoted to physical changes. The simulation of validation used real historical demand trends within the last twelve months, which made the projections to depict the real operating conditions and not ideal conditions (Caron et al., 2000). The sensitivity analysis determined the performance in the case of a change in demand of either + 30 or -30 and ensured that there would be sufficient performance in the event of a possible change in the demand in the future and the design would be effective even with the imminent change in the demand.

Pilot testing within a special facility section allowed validation of the operations and full-scale conversion (Derhami et al., 2020). The organization subdivided the warehouse into three areas deploying optimization layout in Zone 1 (about 120,000 square feet, 33% of the facility) and preserved current layouts in Zone 2-3. The pilot worked eight weeks and gathered specific performance data such as travel distances, equipment use, storage capacity use, order cycle time, and feedback of operator on layout usability (Battini et al., 2016). Simulation predictions were proved right with 7% error in travel distance metrics and 4% in utilization metrics results confirming that the optimization methodology was correct and building management had enough confidence to implement the model on a full scale. Other problems mentioned as operational issues by the pilot were signage inadequacy (equipment at first found it difficult to find the places of their storage in the new design), congestion of cross-aisles during shift changes (equipment movements at the same time creating a point of congestion), and small safety concerns (blind corners on some cross-aisle intersections), which could be resolved with simple corrections before the broader rollout (Derhami et al., 2020).

The gradual implementation, which occurred over a few months, spread disruption over the time, and ensured continuity of the service during the change process (Manzini et al., 2015). After a successful Zone 1 pilot, the organization introduced optimized layout implementation during Zone 2 (weeks 9-16) and completed normal operations in Zone 1 and Zone 3 and subsequently Zone 3 implementation (weeks 17-24). This was a step-by-step method of constrained disrupted area to 33% of facility at any point in time as the capacity was sufficient to meet customer orders during transition. Each step was initiated at the time of seasonal slow (January-February (Zone 2) or May-June (Zone 3)) when the inventory level and the volume of orders were 20-30% lower than the peak, and there was buffer capacity that absorbed any temporary inefficiency in the implementation (Derhami et al., 2020). Six-month transition was longer than technically necessary (it might have been accomplished within 8-10 weeks with uncutting schedules) but offered comfortable buffers eliminating operational hazards and stress of the employees.

The physical layout changes included aisles marking and cross-aisle marking, as well as the identification of storage locations (Derhami et al., 2020). Modifications would be more expensive (possibly $80K-120K to have large facilities) in advanced warehouses with painted floor markings or physical barriers than comparable facilities with flexible marking systems such as floor tape and signage (which may require spending as much as 25K-40K). In the case study, primary aisle markings were provided with industrial floor tape (3M 471 vinyl tape with 100K+ forklift passes) with some painted cross-aisle boundary to guarantee clear visibility and durability at 4-foot widths (Fernando et al., 2021). Storage sites were re-numbered based on new coordinate systems, and databases of the warehouse management system had to be updated (2,856 location records changed), as well as the picker retrained on the new position identification techniques. The company introduced a simple location naming system (Aisle-Cross Aisle-Bay Position format, such as A05-C12-B08 became aisle 5, near to cross-aisle 12, bay position 8) that operators soon mastered, halving the time spent by previous alpha-numeric systems in locating a product (Derhami et al., 2020).

Implementation of operational policy cantered on the use of storage assignment logic alteration in the warehouse management systems (Muppani and Adil, 2008). The improved class-based policy of nearest open location assignment involved programming modifications in site choosing algorithms, which involved distance computations and availability queries.

The implementation process included three steps: first, product classification analysis that defined the best class definitions relying on historical turnover records (finished in 6 hours with automated SQL queries against WMS database); second, zone boundary configuration defining the storage positions range that would be assigned to each class (4 hours with the help of WMS zone management interface); and third, distance calculation logic programming that would allow identifying optimal available positions in a designated zone of each class in real-time (32 hours of Python code development that would be integrated with WMS API and 12 hours of testing and debugging) (Derhami et al The first implementation issues were the accuracy of real-time storage occupancy data (occasional delays between physical inventory and WMS data due to synchronization delays between records caused assignment errors until database refresh rates increased to 30-second intervals) and the need to deal with occasional assignment logic failures when the designated class zones reached capacity (fallback procedures to place the overflow inventory into the next-door class zones with empty capacity avoided operational problems) (Xiao and Zheng, 2010).

➢ *Generalizability Across Warehouse Types and Operational Contexts*

Although the proposed study was done on block stacking warehouses, which are run under the class-based storage policy, the underlying research approach can be applied with proper alterations to different types of warehouses and location settings. Similar structures can be applied to conventional rack-based warehouses, but the rack-specific capacity and accessibility associations are replaced with block stacking formulations (Manzini et al., 2015). Rack systems commit structural frame space to structural frame space, instead of flexible block space, and changes the calculation of space utilization. The analytical aisle optimization model must be changed in such a way that rack aisles will have equipment widths and clearances (11-13 feet with reach trucks and 9-10 feet with block stacking forklifts), a change in value A of the formula $n_a^* = \sqrt{\frac{S_l N_s}{4 S_w A}}$(Derhami et al., 2020). Cross-aisle optimization principles remain largely applicable—creating perpendicular pathways reduces travel distances regardless of storage infrastructure type—though rack systems may impose additional constraints on cross-aisle positioning due to structural integrity requirements.

Automated storage and retrieval systems (AS/RS) bring new design factors such as dedication of aisle to automated equipment, vertical travel elements with mechanized lift systems and optimization of dual command operation where both storage and retrieval operations are part of one equipment run (Manzini et al., 2015). Nonetheless, simulation-based performance analysis and multi objective trade-off analysis are worthwhile methods. The model of optimization of the aisle in the analytical aisle needs to be adjusted to consider the space usage patterns of AS/RS such as aisles taking up a larger proportion of space (aisle-per-column of storage column in manual systems), which could result in improved performance $n_a^* \approx 0.5\sqrt{\frac{S_l N_s}{S_w A}}$with coefficient of adjustment of various geometrical relationships (Derhami et al., 2020). The concepts of cross-aisle are interpreted as transfer stations where automated equipment can move between vertical storage aisles, but the continuous automated operation produces different cost structures with priorities on throughput capacity and less on labor efficiency. The general combination of analysis limits with computational search is conceptually sound, but specific expressions fit the nature of AS/RS operation (Roodbergen & Vis, 2009).

The travel distance properties are different in order picking warehouses where picker-to-product work is a characteristic feature than those of a forklift-based unit-load system, which has been examined in the current research (Van Gils et al., 2018). The speeds of walking (around 3 feet per second) differ significantly with those of a forklift (6-8 feet per second) and change the calculation of the travel times. The capacity constraints restrict the number of items that the pickers can carry at the same time (usually 6-12 items in cart-assisted picking) which result in tour-like routing patterns instead of point-to-point movements that define unit-load operations (Matusiak et al., 2014). Order batching strategies, policies of placing a group of multiple customer orders to be picked simultaneously to enhance efficiency, provide dependencies that layout optimization should be in contact with the batching strategies. The simulation model will have to be adjusted to depict picker motions, consolidation of orders at staging points, and the zone picking strategy where facilities are subdivided into zones served by specific pickers (Derhami et al., 2020). Nevertheless, the underlying framework that compares layout options based on operational simulation and multi-objective comparison can be directly used, and a few studies on warehouse design have indeed applied analogous frameworks to the problem of order picking (Van Gils et al., 2018).

Applications across industries make the process cross-industry, extending to manufacturing warehouses (where temperature zones and energy consumption must be considered), retail warehouses (where mixed pallets and case picking must support store replenishment), cold storage warehouses (where regulatory space must be taken into consideration), and hazardous material warehouses (where special consideration must be taken of regulatory spacing and special safety measures) (Accorsi et al., 2014). Every situation presents distinct limitations and aims energy costs taking over the economics of cold storage, safety regulations limiting hazardous material layouts, case pick efficiency driving retail warehouse designs, though the general approach of systematically creating alternatives, operational performance simulation, and characterization of trade-offs are generally applicable (Derhami et al., 2020). Analytical models and simulation representations should be tailored to incorporate context-specific operational properties of organizations without losing the hybrid analytical-computational approach that allows effective search of complex design spaces.

C. Limitations and Directions for Future Research

- *Model Assumptions and Simplifications Requiring Relaxation*

The study makes a number of simplifying assumptions that are reasonable across a wide range of situations, but might not be accurate or applicable in certain scenarios. The common bay depth policy enforces the same depths in all bays, which makes it easier to implement and less complex to compute (Derhami et al., 2020). Nevertheless, variable bay depths which are optimized regarding product characteristics or space limits may be more performance enhancing. Theoretically, products whose stacking height, turnover, or batch size differed would be well served by customized bay depth allocations, fast-moving low-stack products would be allocated in shallow bays at the aisles and slow-moving high-stack products would go in deep bays in an interior part of the facility (Le-Duc & de Koster, 2005). Future studies would be able to expand the framework to support mixed bay depths and cope with the higher computational load through clever search heuristics (evolution of bay depth patterns using genetic algorithms) or decomposition strategies (finding the optimal bay depths in fixed aisle-cross-aisle structures and then repeating this between layers) (Chen et al., 2011).

The model operates deterministic layout structures and aisle and cross-aisle positions are fixed over planning phases usually on the 3-5 years context of a warehouse design (Derhami et al., 2020). Some real warehouses change layouts on a seasonal basis or when product portfolios change, such as adding temporary aisles in peak seasons, moving cross-aisles in response to a change in product mix, or converting storage to picking in case of an increase in direct-to-consumer order volumes. Various further development includes the use of reconfiguration decisions and transition costs in the dynamic layout optimization, which would establish initial configurations and what should be possible in the future layouts and when transitions should occur (Balakrishnan et al., 2003). These models would trade performance gains with changeover costs such as physical modifiability costs (20K-50K/reconfiguration based on scale), transition costs in terms of operational disruption (could be 2-3 days, partial capacity loss) and retraining needs by employees. This extension needs multi-period simulation models that trace the inventory development over prolonged time (5-10 years) and stochastic optimization planning that address the future demand and product mixture conditions of uncertainty (Caron et al., 2000).

Existing control of material handling equipment presupposes homogeneous shipments and the same abilities of vehicles and the same working speed (Derhami et al., 2020). There are many mixed equipment types used in many warehouses that are standard forklifts (5-6 feet per second), reach trucks (3-4 feet per second), order pickers (2-3 feet per second), and automated guided vehicles (3-5 feet per second and zero labor costs), with various speed profiles, turning radii, lift capacity, and operational capabilities. Heterogeneous fleet models would include equipment-type-specific distance calculations indicating various manoeuvrability constraints (reach trucks with larger turning radii, order pickers with no cross-aisle traversal of pallets), assignment logic to assign each equipment type to a specific movement based on load characteristics and equipment availability, and cost functions reflecting different ownership/operating costs between equipment types (50K-150K annual cost depending on sophistication) (Battini et al., 2016). The complexity of the models could be merited by the fact that the facility has a large equipment diversity and that the vehicle choice has a large impact on both the performance and costs, although the initial analysis indicates that when one equipment type makes 70%+ of all moves, single-fleet assumptions are accurate enough estimates (Derhami et al., 2020).

The model presupposes stable demand trends and products lines, and maximizes the average conditions, but not peak scenarios or seasonal changes (Derhami et al., 2020). Warehouses with 2-3 times demand variation in normal and peak periods may need designs with surge capacity which may prefer layouts with higher utilization in average periods, and tolerate some congestion in peaks, instead of excessively providing capacity in the infrequent extreme conditions. To explicitly capture the uncertainty in demand, future studies can be based on chance-constrained modeling in which layouts satisfy service level requirements with given

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confidence levels (e.g., probabilistic 95% accuracy of addressing the demand within target cycle times) over stochastic demand conditions (Matusiak et al., 2014). This would produce layouts resistant to changes in the operations at the expense of worse-case performance. The trade-off between the average performance optimization and robust design is worth exploring especially in cases of warehouses that are used in product launching, seasonal shops, or any other environment where the demand is volatile.

➢ *Extensions Incorporating Additional Performance Dimensions*

The existing structure maximizes the space usage and the distance travelled and considers other performance aspects as limitations or non-priority. There are several other goals that should be specifically included in long-term models (Derhami et al., 2020). Safety of operators, fatigue, and risk of injury is growingly becoming a key issue of ergonomics in manual warehouses where worker wellbeing impacts both the ethical consideration and cost of operations through compensation of injuries, turnover, and productivity. Layouts necessitating regular long-distance walking (5+ miles per day) or discomforting reaching movements (placing overhead more than 6 feet above floor, retrieving items lower than 2 feet above floor) are costly to humans in terms of human costs (Battini et al., 2016). Layouts that optimize productivity and worker wellbeing would be found by multi-objective models that add ergonomic measures, such as cumulative daily walking distance, proportion of movements involving non-neutral postures, and frequency of heavy lifting operations, and have efficiency goals. Over the ergonomic constraints, moderate bay depth (limited reaching distance), wide aisle (manoeuvring difficulty), and cross-aisle networks (minimised cumulative walking distance) would be favoured (Derhami et al., 2020).

Service level targets and throughput capacity should be explicitly treated instead of being tacitly handled through constraints of vehicle requirements (Matusiak et al., 2014). Warehouses with strict order cycle time requirements (same-day shipping with 2-hour fulfillment) or throughput requirements (at least 5,000 orders per day) need layouts that will provide sufficient capacity during peak operations, not average operation. Laying out with layouts that satisfy service level goals at given confidence levels (e.g., 98% of orders met within target cycle times) amid demand uncertainty could be identified using formulations of chance-constrained optimization, which might be prepared to accept a higher average cost to achieve higher reliability (Derhami et al., 2020). This method directly measures capacity reliability trade-offs versus cost factors so organizations can make sensible decisions regarding how much quality care to pay to guarantee better service provision. The performance measures (percentile) used in the methodology would be that the layouts are acceptable to handle high demand situations even in scenarios where averages are good (Caron et al., 2000).

The demand of environmental sustainability such as energy use, carbon-based emissions, and resource use is becoming a central theme in the design of the logistics system, with organizations seeking to achieve environmental, social, and governance (ESG) objectives (Accorsi et al., 2014). Travel distance is correlated with material handling equipment energy consumption but with non-linear relationships with acceleration (that requires 3-4× steady-state power in the first movement), loaded versus unloaded movement (loaded movement that consumes 40-60% more energy), and idle time (consumes 15-25% of active power even when idle). Layouts that reduce environmental impacts using explicit energy models of these behaviors may be able to measure the sustainability-cost trade-offs (Derhami et al., 2020). Early evidence is that energy-optimal layouts are like travel-optimal layouts except that the acceleration curves are smoother by allowing larger aisles and long clear paths, which may be allowed to increase travel distance by 2-3% to eliminate stop-and-go profiles by 15-20%. These extensions would be useful in organizations that seek to achieve carbon neutrality goals or announcements such as the warehouse energy emissions standards in California which demand energy cutbacks of 5-10% every year (Accorsi et al., 2014).

➢ *Advanced Optimization Algorithms and Solution Methods*

Although the existing structure uses full enumeration of constrained design spaces with simulation analysis, big issues or long models with other decision variables may be addressed with more sophisticated metaheuristic optimization methods (Derhami et al., 2020). Layout populations could be evolved with genetic algorithms using crossover operations (taking aisle layouts of parent layouts and cross-aisle locations of other layouts) and mutation operations (randomly changing bay depths or cross-aisle locations), which may find novel layouts absent in systematic enumeration. Simulation-based fitness assessment would be used to direct evolutionary inquiries to solutions that perform well, and Pareto dominance relations between solutions would keep frontier variety (Hu and Chuang, 2022). The technique may efficiently search larger design spaces (100,000+ candidate solutions) than exhaustive enumeration, but the complexity of implementation is much greater and the quality of solutions is not as guaranteed as in exhaustive algorithms.

The probabilistic local optima escape of design spaces by simulated annealing methods could guide these methods to avoid inferior solutions that would trap greedy search strategies (Palubeckis, 2017). The acceptance probability parameter would reduce with increasing iterations (geometric cooling schedule with) $T_{k+1} = 0.95T_k$ step-by-step narrowing down the search direction with temperature 5% cutoff), slowly targeting promising areas. First high temperatures allow wide exploration with 20-30% worse performance than current best, and final low temperatures only allow 1-2% degradations to guarantee high-quality solutions (Derhami et al., 2020). Similar implementations might be done at scale and assess a collection of candidate solutions in parallel on distributed computing resources, using the capabilities of modern cloud infrastructure to run 100 or more parallel simulations. Nevertheless, simulated annealing is stochastic and therefore requires parameter tuning (initial temperature, cooling schedule, number of iterations) that is problem-dependent and can be extremely time-consuming in both computation time and number of

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experiments that may not guarantee improvements over systematic enumeration (Chen et al., 2011).

Tabu search keeping records of recently-considered solutions may avoid cycling (inspections of already-inspected design regions) and promote extensive search through various design areas (Arnaout et al., 2017). The tabu list captures recent layout changes (e.g. "aisle count increased to 6" is tabu to be undone 7 times before it can be undone), and thus requires exploration of areas not previously explored to find out to the searcher who may not find the immediate neighbours attractive. Tabu moves are enabled by aspiration criteria that find solutions that are better than existing best to ensure that excellent configurations are not recreated by tabu restrictions (Derhami et al., 2020). Adaptive tabu tenure (increasing/decreasing list length depending on the progress of the search) is a balance between intensification and diversification around good solutions versus exploration of remote areas. Early trials indicate that tabu search finds solutions in 3-5% of known optima with only 40-50% the number of simulations than complete enumeration applied to 500+ SKU problems, but until more development resources are devoted to it, the implementation complexity and sensitivity of parameters to solution are limiting its practical use (Zhang and Li, 2024).

D. Concluding Remarks

The study came up with and proved the existence of a modeling and intuitive simulation-based optimization system to design warehouse layouts that optimize the use of storage space and at the same time reduce the distance of material collection and delivery. The combined methodology is an analytical-modeling that identifies the optimal aisle layouts, a discrete-event simulation that models stochastic operational behaviors of the facility, and a multi-objective optimization that finds Pareto-optimal solutions to the facility layouts. It was applied to a real-world case study of a beverage warehouse and showed a significant improvement in operations with the best layout showing an over 10% reduction in the costs of material handling although 10% space was sacrificed bringing annual savings of more than 550,000 dollars.

The theoretical model that develops closed form solutions to the optimal number of aisles offers both practicable design advice and theoretical basis to computational optimization. The expression $n_a^* = \sqrt{\frac{S_l N_s}{4 S_w A}}$ enables quick initial design evaluation and puts strict constraints on scenario generation. Improved class-based control of storage policies that combine closest open location assignment inside a specified area reap the advantages of strategic placement and tactical distance reduction, and are always more successful than the traditional random within-class options by 15-30%.

The multi-objective optimization model explicitly defines trade-offs between objectives to compete, which create Pareto frontiers to make decisions based on a variety of cost structures. Sensitivity analysis has shown that there is a significant variation in optimal configurations between cost situations and it is space-cost-dominant contexts where dense storage layouts are preferred and handling-cost-dominant contexts where travel-optimal configurations with broad cross-aisle networks are favored. The structured approach offers managers in the warehouse with quantitative design support tools, as opposed to using intuition and experience.

Future research avenues involve the simplifying assumptions like common bay depths, homogenous equipment fleets, as well as adding other performance goals like ergonomics and sustainability, and creating better optimization algorithms with better computational efficiency. It would be better to have extensions to dynamic layout optimization to cover periodic choices in reconfiguration and multi-period planning horizons to improve applicability to changing operational situations. The devised framework is a major step forward in the methodology of warehouse design despite the limitations that are presently being faced, and it offers integrated optimization possibilities that have not existed before in the research literature or practice.

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