Simulation Modelling Practice and Theory 133 (2024) 102902

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

Assignment-simulation model for forklifts in a distribution center with aisle constraints

Mauricio Becerra-Fernandez [a,*], Olga R. Romero [a], Johanna Trujillo-Diaz [b], Milton M. Herrera [c]

[a] School of Engineering, Science and Technology, Universidad del Rosario, Bogotá, Colombia
[b] Fundación Universitaria Internacional de La Rioja - UNIR, Bogotá, Colombia
[c] Faculty of Economic Science, Universidad Militar Nueva Granada, Bogotá, Colombia

A R T I C L E I N F O

Keywords:
Discrete-event simulation (DES)
Forklift
Logistics
Resource allocation
Warehouse

A B S T R A C T

This study proposes a simulation model for allocating counterbalanced forklifts in a logistics distribution center (LDC) with aisle constraints. Modeling the case study for a consumer goods firm, the performance measures of the logistics operation were calculated and certain experimental scenarios were purposed for decision-making regarding the number of forklifts and their productivity. The relevance of this research is validated by the gap in existing literature on enhancing forklift assignments in massive storage systems with restrictions. The simulation scenarios contribute toward standardizing logistics operations with similar characteristics, starting from the layout stage of an LDC. The designed simulation model demonstrates that the simulated allocation incorporates technical and human resources in warehouse operations. Utilizing discrete-event simulation (DES) as a framework, this study assesses various scenarios in an LDC with restrictions on the forklift. The hypothesis of the problem was analyzed, and the simulation model was used to characterize the system behavior under different scenarios and guide the decision-making processes impacting operational costs and client service levels. This research employs DES to address performance indicators and operational costs, serving as a methodological guide for resource allocation in logistics operations at distribution centers.

1. Introduction

Contemporary logistics firms are confronting global challenges that influence midterm operational costs. The COVID-19 pandemic, global market integration, logistics networks, and the transition to sustainability pose substantial challenges, diminishing business competitiveness. Specifically, in Latin America, the Inter-American Development Bank reports that the logistics performance of the region significantly lags behind other nations [1]. This decline relative to previous periods profoundly affects the ability of organizations to navigate uncertainty and fluctuating demand.

The Development Bank of Latin America, formerly known as the Andean Development Corporation (CAF), examined Latin America's logistics profile, focusing on infrastructure, services, processes, information systems, management, institutional framework, and regulation. This analysis revealed a paucity of genuine logistics operators and a notable scarcity of logistics platform development projects [2]. These findings underscore the necessity of fostering academic research projects to conceive new logistic strategies.

* Corresponding author
E-mail address: mauricio.becerra@urosario.edu.co (M. Becerra-Fernandez).

https://doi.org/10.1016/j.simpat.2024.102902
Received 10 July 2023; Received in revised form 22 December 2023; Accepted 26 January 2024
Available online 6 February 2024
1569-190X/

The National Council for Economic and Social Policy published the 2020 logistics performance index survey results. Among the 160 participating economies, Colombia ascended to 58 th place, an improvement of 36 positions from the preceding survey. The survey denoted an increase in national logistics performance from 13.5 % in 2018 to 12.5 % in 2020, even as logistics investments grew by 8 %–10 % of firms' revenues [3]. Notably, the logistics cost component represents the most significant decline in sales at the business level. This research addresses the cost implications for logistics operators, warehouses, and associated technologies.

In the 2020–2021 timeframe, the Global Competitiveness Report revealed that 64 % of Colombian companies lacked technological tools for logistics processes. The logistics performance index score for this period was a modest 2.94 out of 5, trailing behind nations like Mexico, Brazil, and Chile [4]. This situation underscores the marked uncertainty faced by logistics firms, largely attributed to the variations induced by the COVID-19 pandemic. Thus, a pressing necessity emerges to investigate the performance of logistics operators amidst fluctuating demand spikes.

The aforementioned challenges necessitate focused attention on planning logistics processes across supply chain levels. Thus, effective management is crucial for achieving improved results at reduced costs, ensuring business sustainability, and enhancing end-consumer performance.

In logistics distribution centers (LDCs), the complex interplay of labor, equipment, and consecutive processes complicates resource allocation. Within this operational framework, discrete-event simulation (DES) is instrumental for evaluating performance management [5]. This study employs simulation methodology to assess logistics operations in an LDC, specifically addressing forklift assignment problems in LDCs with restricted aisle dimensions, and proposing an assignment model via a DES approach.

The simulation scenarios enhance understanding of the logistics system behaviors and resource allocation in the design of logistics operations [6]. Although previous studies leverage simulation modeling for logistics facility design, only a few have examined the impact of aisle dimension restrictions with diverse forklift types. The present study addresses this gap in the literature. Additionally, it offers a practical contribution by providing a simulation-based framework to analyze performance in logistics facilities with spatial constraints.

This research aims to facilitate the application of DES in distribution centers, specifically in the allocation of various logistics operation resources. It examines the interplay between capacity and demand in achieving customer service levels, while considering the costs incurred by the logistics operator.

The remainder of the paper is organized as follows: the existing literature on the analysis of logistics resource allocation (technical and human) is reviewed in Section 2. The used simulation model as well as the system's performance indicators are introduced in Section 3. The results obtained and alternatives proposed to improve the logistics operations are presented in Section 4. The key findings are discussed in Section 5, and the conclusions and future works are presented in Section 6.

2. Literature review

The literature review aims to explore similar applications in resource allocation at distribution centers, employing different techniques and emphasizing the advantages of using DES. This review collates contemporary studies pertinent to this research, focusing on aspects such as citations, methodologies employed, variables analyzed, validation processes, performance measures, and significant findings. This comparative analysis enhances the context of this study. The literature review was conducted using Web of Science and Scopus, identifying 31 articles with the search equation: (*warehouse OR stockroom OR storehouse OR stockpile OR "distribution center"*) *AND simulation AND* (*"forklift truck" OR forklift OR "forklift" OR "stacker truck"*). To identify the trends in this domain, six clusters were identified using VOSViewer, also enabling a temporal evolution visualization (refer to Fig. 1).

1. Warehouses design (green cluster).
2. Forklifts assignment (light blue cluster).
3. Routes design for forklift assignment using optimization and heuristic techniques (dark blue cluster).
4. Warehouse management models (yellow cluster).
5. Design of DES models using Petri nets (purple cluster).
6. Warehouses design with a sustainable approach (red cluster).

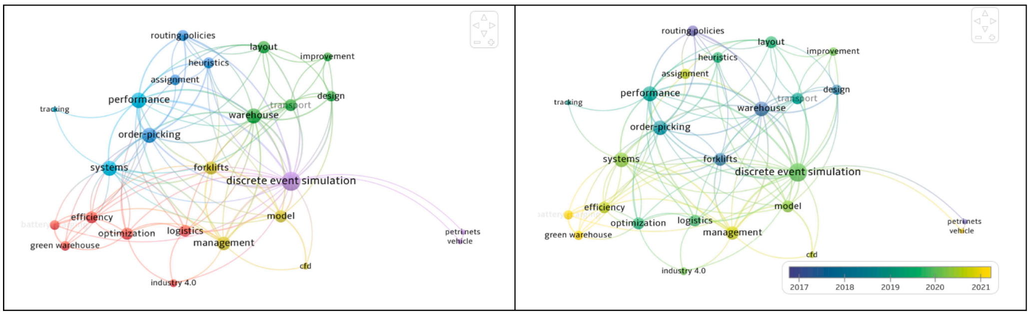

Fig. 1. Left: visualization of six clusters extracted from the literature review; right: clusters visualized by year.

The literature review (LR) did not adhere to specific inclusion criteria. The articles identified through the search equation spanned from 2007 to 2020. The distribution of publications was as follows: 30 % between 2016 and 2019, 25 % in 2020, 20 % in 2021, and 10 % in 2022. A significant proportion of these articles originated from Europe (notably Croatia and Italy), followed by the Middle East (30 %), and the USA (10 %). Among the 31 articles reviewed, the top 10 (refer to Table 1) accounted for 80 % of the citations, totaling 478 citations (refer to Fig. 2). The most cited authors were [7] and [8].

In the LR, the use of discrete events simulation (DES) [7,9–22] was covered in 25 articles for warehouse management, which focus on different objectives: a) warehouse design [9,23–25] and its shelves [25]; b) planning shorter routes for forklifts [7,8,10,11,14,20–27], using multiple types of AGV forklifts [7,8,11,18,19,22,24,25,28–30], cranes [29] or forklifts [8–14,17,19,20,22,24,26,27,29,31–35], powered by hydrogen [12]; c) selection of storage positions [26]; d) location areas [22,31], and wireless charging [19] for them within the warehouse. In contrast, the supply chain (SC) has been modeled using DES for estimating the materials mobilization efficiency and storage, the technique is value stream mapping [21].

In the LR, the DES models were primarily modeled in the following software: EXTENDSIM8 [33], Montecarlo simulation [35] using a solver in Microsoft Excel [30], Technomatix Plan Simulation software [13], Pawel Zajac Method [34], and FlexSim [30].

The LR on DES for estimating the use of forklifts in warehouses, these techniques have been combined with other statistical, optimization, and probabilistic techniques for decision-making and minimizing uncertainty. The hybrid techniques include a) data mining such as the multidimensional scaling algorithm [23] and statistical analysis of least squares [22]; b) optimization [9,16,18,19,27] using the Dijkstra algorithm [24], linear programming [18,19,30], mixed integer programming [28], among others specifically for forklift routes design, the vehicle routing problem [23], with time windows [7], EKF filtering algorithm [6], which can optimize the mobilization and positioning system, quadratic allocation (QAP) [9], such as using a single, discrete particle swarm genetic algorithm (DPSO) [9], dynamic programming [16] or Petri nets [11,29]. A dynamic and periodic programming model is proposed to design routes for AGFs using a programming model with time windows—a periodic dynamic replanning of time sequences—to avoid blockages [36]. In contrast, c) probabilistic theories such as Markov processes [16], computational fluid dynamics (CFD), and Bayesian networks [37].

In these simulation models for resource allocation, at least one performance measure should be incorporated to assess the proposed scenarios against the current state of the logistics facility, along with relevant input variables to define the simulated model. The related studies can be categorized based on the input variables and performance measures considered (refer to Table 2).

In the LR, the DES has been used to assess sustainability [28,37] using forklifts in warehouses and estimate: a) the environmental impact and contamination [19,37] caused by the emission of hydrogen [12,35,39]; b) the use of energy [19] and batteries recharging [28,30,34]. An emerging research area involves simulating forklifts with noncontact static and dynamic electrical power transmission technology, where magnetic coupling between underground coils and a vehicle-mounted coil reduces battery reliance and recharging downtime, potentially enhancing resource productivity through new technology adoption [19].

There are two types of scope for the development and validation of DES models, considering other techniques to estimate the use of forklifts in warehouse management: a) experimental [12,18,22,29,30,32] and nonexperimental. For the latter, extensive experiments are conducted in real warehouses to validate the effectiveness of the algorithms or simulations [8,22]; the two specific cases reported in the literature for warehouses were 4000 m2 [14] and 45.4 m^3 [12]. In contrast, forklifts have been applied in warehouses for crops [32], hospitals and tug trains [11], tires [19], and aerospace components [15], among others in European factories [7]. However, the scope of the DES is used to estimate the vibration of the steering wheel of faulty forklifts at idle, including the Hilbert Huang transformation method [17].

LR underscores research in warehouse design, forklift assignment, and route planning, with a focus on sustainability. However, these studies do not provide detailed steps for using discrete simulation in resource allocation within logistic distribution centers, which is addressed in this paper.

3. Methodology

The development of the methodology presented herein aims to provide guidance on using DES for allocating various resources in

Table 1
Top 10 citations from the literature review.

Cite	Title article	Citation
Smolic-Rocak, N, 2010	Time Windows BaDES Dynamic Routing in Multi-AGV Systems	92
Estanjini, 2012	A least squares temporal difference actor-critic algorithm with applications to warehouse management	11
Houf, 2013	Hydrogen fuel-cell forklift vehicles release in enclosed spaces	25
Burinskiene, 2015	Optimizing forklift activities in wide-aisle reference warehouse	12
Draganjac, I, 2016	Decentralized Control of Multi-AGV Systems in Autonomous Warehousing Applications	104
Ma, 2017	Fusion of RSS and Phase Shift Using the Kalman Filter for RFID Tracking	46
Burinskiene, 2018	a simulation study for the sustainability and reduction of waste in warehouse logistics	23
Yener, 2019	Optimal warehouse design: Literature review and case study application	32
Barral, 2019	Multi-Sensor Accurate Forklift Location and Tracking Simulation in Industrial Indoor Environments	23
Abideen, 2021	Improving the performance of a Malaysian pharmaceutical warehouse supply chain by integrating value stream mapping and discrete-event simulation	18
	Others	92

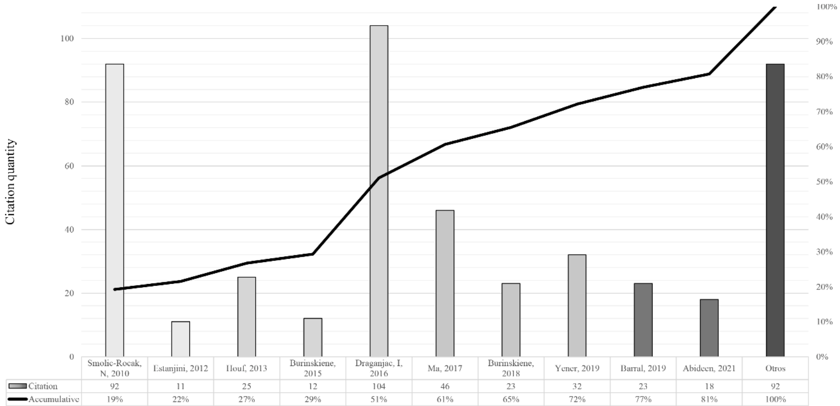

Fig. 2. Pareto analysis for authors, years, and citations.

Table 2
Input variables and performance measure from the literature review.

Inputs variables	Performance measures for DES modeling
Inventory [20,25]	Resupply Cost [24,27]
Material handling capability [8,11]	Quantity of orders [11,33]
Number of forklifts [8,11,13,27]	Forklift size and programming policies [11]
Forklift size [8]	Mobilization risk policies [37]
Quantity and dimensions of the aisles [25–27,32]	Total work cycle time for forklifts [33]
	Warehouse utilization level [25]
Average order fulfillment time [23,24,27]	Decentralization and private forklift maneuvering areas [8]
Charge and discharge time [14,33]	
Human resources assignment [38]	Efficiency [25,33]
Dock doors assignment [11,30]	Minimize cost [16,19,28]
Work shifts [38]	Operational and logistics costs [10,34]
Traffic rules [11,14]	Management [9]
Speed [11,14,18,22]	Mobilization time [18,26]
Material flow volume [27]	Cargo and space [26]
Deadlock, obstacles, corridors, and crowded spaces [8,29]	Distance [20,25]
Warehouse size [12,14]	
Quantity, dimensions, and location of slots [14,25,32]	
Slot capacity [25]	
Risks and failures of mobilization of chemical products due to forklifts and dangerous goods [9,37]	
Ventilated hydrogen deflagration risks [12]	

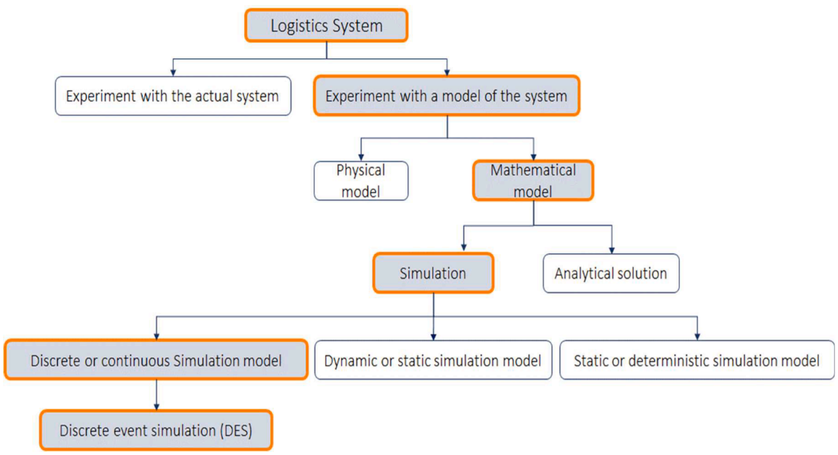

Fig. 3. . Selection of methodological design.

distribution centers, including personnel, equipment, machines, and tools, tailored to the specific requirements of logistics processes. The selected methodological approach is outlined as follows:

3.1. Methodological design

The input data of the simulation model were sourced from one year of historical records, extracted from the warehouse management system and processed using Microsoft Excel. Fig. 3 illustrates the proposed methodological design for constructing the simulation model. This approach involves using simulation models to conduct experiments within the logistics system, thereby avoiding additional costs. Based on historical data and the definition of discrete variables, these models are complemented with mathematical simulations. The process typically initiates with a conceptual model, representing a set of entities (facilities or processes) that interact to achieve a common objective.

Systems involve either experiments with the real system or simulations of the system [40]. Consequently, the simulation model mirrors the characteristics of the system, replicating the behavior of the physical system under operational conditions. Direct experiments with real systems are less frequent owing to their heightened sensitivity to minor variable variations, which can increase operational costs. Therefore, the experimentation employs a generic forklift assignment model, adaptable for other organizations with characteristics similar to those studied.

The steps to construct the simulation model are presented in Fig. 4, which are typically utilized in the DES modeling to analyze the system behavior [38,41]. Note that the steps of DES methodology are determined by the set of logical, mathematical, and probabilistic relationships that integrate the system behavior in the occurrence of a given event. The steps of the DES methodology defined for this paper are observed in Table 3.

3.2. Problem formulation

The warehouses for LDCs with narrow aisles pose unique challenges for forklift operations, especially when only one forklift can be utilized per aisle. This paper assesses the impact of such spatial constraints on LDC operations and examines the performance measures to enhance logistics processes such as picking, loading, and unloading.

3.3. Hypothesis definition

The simulation scenarios were designed based on the quantity of counterbalanced forklifts, segmented into two groups based on the objectives and hypotheses of the study, as summarized in Table 4.

3.4. Conceptualization of model

The conceptualization of the model considers operations tailored to warehouse types, based on the nature of the stored goods. In this instance, the study focuses on a finished product warehouse, a typical format serving as an intermediary between various industrial activities. This warehouse encompasses general areas for pallet unloading, transfers, storage, replenishments, and dispatches, as depicted in Fig. 5.

3.4.1. Unloading of vehicles

The primary aim of the operation is to unload pallets from vehicles using counterbalance forklifts. This process commences with

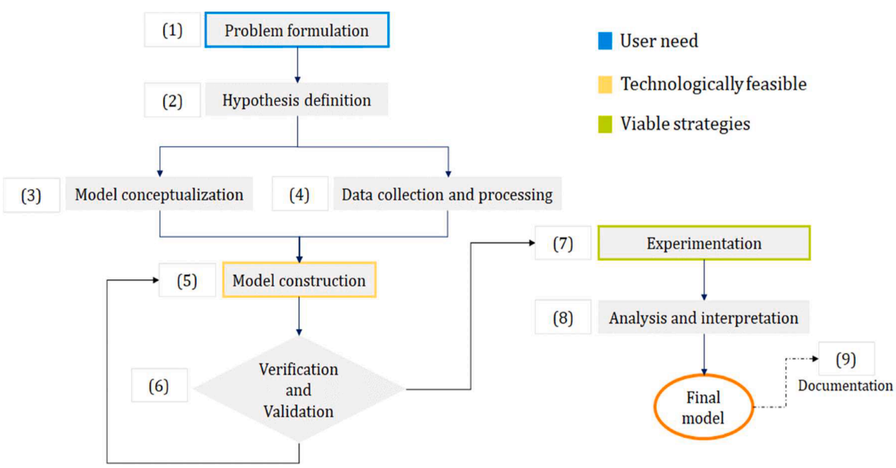

Fig. 4. Selection of methodological design DES.

Table 3
Stages of discrete-event simulation (DES) methodology.

No.	Stage	Description	Application to logistics warehouses
1	Problem formulation	The simulation problem to be solved is defined, considering that simulation can be used to evaluate, predict or analyze the behavior of variables in a system.	Identify the answers to be obtained with the simulation model, related to the number of resources to be allocated by resource type.
2	Hypothesis definition	The researcher defines the assumptions about the expected behavior of the system. These assumptions will then be compared with the final simulation results.	Define the arguments to be evaluated related to the allocation of resources in the distribution center.
3	Conceptualization of the model	The components or operations that are part of the system are organized, taking into account that they can affect the variables under study.	Identify process flows, the intervention of resources to be allocated, along with data sources of processing times by activity.
4	Data collection and processing	With the preliminary design of the system to be simulated, qualitative and quantitative information is collected. The information can be extracted from primary and secondary sources, such as documents, interviews with experts, observations, or measurements on the object of study.	Collect sufficient and reliable data based on statistical methods. Considering conventional data sources in the process or data collection needs.
5	Model translation	The data collected in advance are coded and then processed in the simulation software selected by the researcher. Identify the main components of the initial model.	Use a user-friendly simulation language in accordance with the level of knowledge of the engineers in the logistics process.
6	Verification and validation	With the data in the system, the behavior of the model is verified, and the results are following the expected behavior based on the initial hypotheses of the model.	Compare the results of the initial simulation model with respect to the historical data of the process and that they are consistent with the consistency defined by the engineering team.
7	Experimental design	The model runs allow you to define how many scenarios you want to validate, according to the model components and the comparative strategies of the resources you have, for a change model.	To find the statistical robustness of the model developed, generating confidence in the simulation process carried out in the distribution center.
8	Analysis and interpretation	Based on the results of the simulation, the behavior of the model is analyzed to determine the ideal scenario to guide decision-making within the LDC under study.	The scenarios should allow for rebutting the arguments put forward with respect to the allocation of the various types of resources.
9	Documentation	Finally, the methodological design ends with the documentation of the model indicating the recommendations and quantitative conclusions reached with their respective analysis.	The documentation should allow replication of the simulation model under similar circumstances, as well as allow adjustments to be made to the scenarios and guide the simulation in similar processes.

Table 4
System hypothesis.

Scenarios	Description of the scenario	Objective	Hypothesis
1, 2, 3, 4, 5	One counterbalanced forklift team is assigned, combined with 3,4,5,6, and 7 retractable forklift teams.	Include forklift equipment to comply with aisle restrictions.	Greater number of counterbalances and reach trucks correspond to superior performance of the logistics operation.
6, 7, 8, 9, 10	Two counterbalanced forklift trucks are assigned, combined with 3,4,5,6, and 7 reach trucks.	Include two forklifts to improve the number of pallets dispatched.	

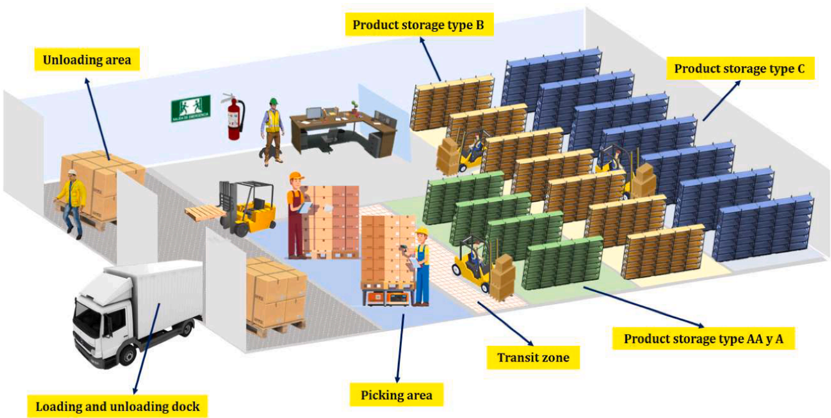

Fig. 5. LCD general operations.

Table 5
Forklift equipment datasheet.

	Counterbalance forklift	Retractable forklift
Image		
Description	These forklifts are characterized because they have a counterweight in the rear area and a support point for the loads in the front area. They are used for loading and unloading; therefore, they represent the most conventional types of forklifts.	Forklifts are characterized by performing displacements and turning maneuvers by retracting a mast. These are characterized by having less weight and moving in narrower aisles; therefore, they represent the type of forklift with good performance.
Operating system	Manual	Manual
Lifting height	7.50 m	8.50 m
Aisle dimensions	3.20–4.00 m	2.70–2.80 m
Storage system	Selective shelving Drive-in shelving –	 Dynamic shelving

Adapted from MECALUX: Storage systems.

pallet unloading for storage, culminating when the pallets are positioned in the transit zone. In the receiving area, an operator inspects the pallets before transferring them to the transit area.

3.4.2. *Transfer to picking area*

The objective of the second operation is to relocate pallets from the transit to the picking area using reach trucks. This is achieved based on the product classification within each rack. The filling begins at the lower levels of the racks, with products sorted by type and rotation frequency, placed near the staging areas and loading docks for easy access.

3.4.3. *Transfer to storage area*

The third operation aims to move pallets from the transit zone to the storage zone using retractable forklifts. These forklifts allocate products according to predefined storage zones in the layout for each product type.

3.4.4. *Replenishment*

The fourth operation involves replenishing products from the second level or higher in the picking zone to the first level and restocking products from various storage areas to the picking area, utilizing reach trucks.

3.4.5. *Dispatch*

The objective of the fifth operation is to transport full pallets from the storage area to the loading docks using reach trucks, considering the location and maneuvering of the pallets. According to historical data, 78 % of the products are shipped as full pallets, whereas the remaining 22 % comprise incoming boxes.

3.5. *Case study*

This methodological model was applied in a case study at a leading LDC in the consumer goods sector.

The general characteristics of the LDC include: (1) a double linear distribution by the logistics operator; (2) restricted aisles; (3) the

Table 6
Product classification by percentage of sales.

Product type classification	Percentage of sales	Capacity Level 1 (pallets)	Capacity level 2 and above (pallets)	Total capacity (pallets)
AA	41.22 %	251	1186	1437
A	38.02 %	231	1094	1325
B	16.26 %	99	468	567
C	4.50 %	27	130	157
Total	100 %	608	2878	3486

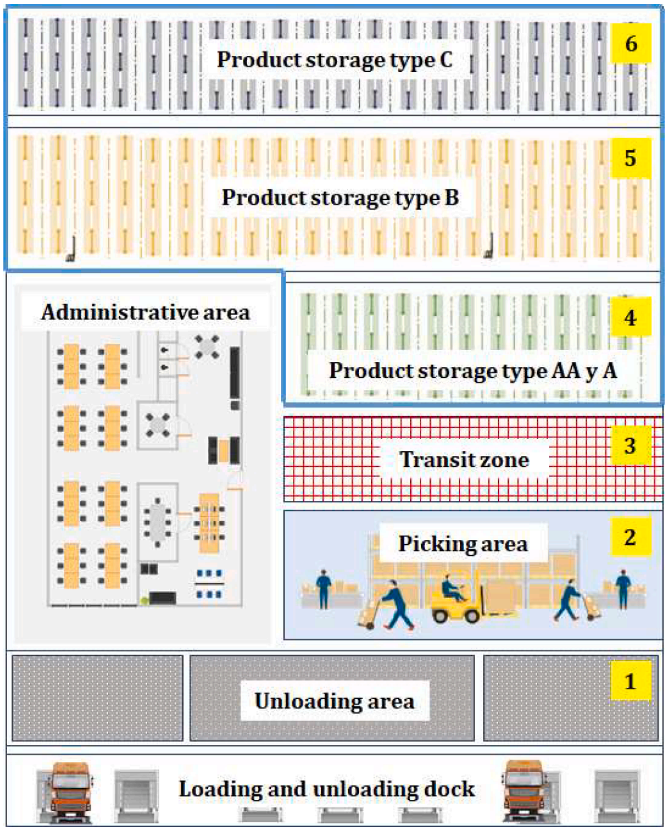

Fig. 6. General layout of the LDC. (4) Storage area for type AA and A products. (5) Storage area for type B products and (6) mass storage area for type C products.

Table 7
Number of observations (n′) of the preliminary study.

Forklift	Variables	n'
Counterbalanced	Unloading	30
	Pick-up	30
	Placement	30
Retractable	Pick-up	25
	Placement	25
	Loading	15

use of two types of forklifts, as detailed in Table 5; (4) an expected service level corresponding to the throughput value of the simulation; (5) the execution of operations such as vehicle unloading, transfer to the picking and storage areas, replenishment, and dispatch.

The pallet storage in the LDC is organized by classifying products into four types: AA, A, B, and C. This classification is based on the percentage of sales each product type contributes to the total stock. The allocation process involves categorizing and defining product importance according to their sales percentage, as expressed in Table 6.

The layout defined and the processes conducted within the LDC operation are described below.

· LDC layout

The warehouse distribution has a total LDC area of 13,792 m2 comprising six areas: (1) unloading area: 2522 m2. (2) Picking area: 2355 m2. (3) Transit area: 420 m2. (4, 5, and 6) storage area depending on the type of product.

The storage area of the logistics operator represented by areas 4, 5, and 6 corresponds to 8495 m2 arranged to store four types of products (refer to Fig. 6).

Table 8
Several observations (N) with statistical method.

Forklift	Variables	N
Counterbalanced	Unloading	46
	Pick-up	55
	Placement	39
Retractable	Pick-up	31
	Placement	45
	Loading	21

3.5.1. Data collection

The data collection and analysis provided statistical robustness of the simulated model, allowing to correctly represent the logistics operation and subsequently evaluate scenarios. In the collection and analysis of system variable times, the number of preliminary study observations can be empirically determined by process expertise. However, for this research's time study analysis, the standardized guide of approximate values from The General Electric Company is referenced [42]. According to the recommended number of observation cycles (n′), the following values are considered for each variable, as observed in Table 7.

The sample size for preliminary observations is calculated using methods such as statistical and monographic approaches. This study utilizes the statistical method formula (refer to Eq. (1)), considering a 95 % significance level and a margin of error of $+/-$ 5 % [43].

$$n = \left(\frac{40\sqrt{n' \sum x^2 - \sum (x)^2)}}{\sum x} \right)^2, \tag{1}$$

where

n : size of sample to be calculated (number of observations).

n' : number of observations of preliminary study.

x : value of observations.

40 : constant for a confidence level of 95%.

Applying Eq. (1), we obtained that if the number of observations is less than the required number, this time-taking must be completed considering the observations (N) (refer to Table 8).

Following new model runs, the study proceeds with independence tests for the times of each variable. A summary of the results obtained from these tests is listed in Table 9.

To validate the independence property of the data set, the following hypotheses for the model are formulated:

- $H0$: The times of the number of observations are independent.
- Hi : The times of the number of observations are not independent.

If the calculated value exceeds the theoretical value (refer to Table 9), it indicates that the numbers in the analyzed set are not independent. The test employed an alpha value α =0.025, corresponding to a significance level of $Z_\alpha = 1.96$ according to the number of observations of each variable.

Utilizing the Stat Fit program, the independence test concluded that H_0 should be accepted because the calculated value (*p*-value) is lower than the theoretical value (level of significance). Therefore, the times of all observations (n) are independent. An example of the independence test applied to each variable in the model is available in the appendix (Figs. 10 and 11)

The goodness-of-fit test results listed in Table 10 determines the probability distribution. An example of the application of these tests for one of the six variables of analysis of the model are referred in the appendix (Figs. 12and 13)

Table 9
Independence test (summary).

	Time counterbalanced forklift			Time retractable forklifts		
Variables	Unloading	Pick-up	Placement	Pick-up	Placement	Loading
Data points	46	55	39	31	45	21
Points above median	23	27	19	15	22	10
Points below median	23	27	19	15	22	10
Total runs	25	31	20	12	21	8
Mean runs	24	28	20	16	23	11
Standard deviation runs	3.353	3.639	3.040	2.690	3.277	2.176
Runs statistic	0.298	0.824	0.000	1.486	0.610	1.378
*Level of significance	1.960	1.959	1.959	1.959	1.959	1.959
*p-value	0.766	0.409	1.000	0.137	0.541	0.168

* p-value: calculated value; * level of significance: theoretical value.

Table 10
Goodness-of-fit test (summary).

	Counterbalanced forklift			Retractable forklift		
	Unloading	Pick-up	Placement	Pick-up	Placement	Loading
Distribution	Lognormal	Normal	Beta	Johnson SB	Weibull	Logistic
Rank	98.9	100	100	100	100	94
Minimum	−180,892		0.751	0,957	0.499	
Maximum			1.719			
Mean		0.997				
Alpha					7.396	2.495
Beta					0.522	7.175
Gamma				−0,106		
Delta				0,772		
Lambda				8.18E-02		
Sigma	6.72E-04	4.45 E-02				
Mu	5.203					
P			1.029			
Q			2.9			

Table 11
Elements included in the construction of the simulation model.

Element	Quantity
Locations	249
Entities	3
Types of resources	2
Networks	2
Nodes	157
Attributes	3
Variables	6
Shifts	2
Macros	8

Table 12
Variables of simulation model.

Acronym	Name of Variables	Description
UCF	Unloading time for counterbalanced forklift	Time spent by the counterbalanced forklift in the process of unloading pallets from the docks to the transit area.
PCF	Pick-up time counterbalanced forklift	Time spent by the counterbalanced forklift in the process of picking up the pallets going to the transit area.
LCF	Counterbalanced forklift placement time	Time spent by the counterbalanced forklift in the process of locating the pallets in the picking area.
PRF	Pick-up time retractable forklift	Time used by the forklift truck to pick-up pallets from upper levels.
RFL	Retractable forklift placement time	Time spent by the reach truck in the process of locating the pallets to be taken from the transit area to the picking area.
LRF	Loading time of retractable forklifts	Time used by the forklift truck in the loading process of the pallets being shipped.

3.5.2. Translation of the model

The summary of the number of elements in the simulation model is listed in Table 11.

3.5.3. Model components

The components of the model under evaluation are described in Table 12.

3.5.4. Performance measures

For the analysis of the simulated system, the following three main performance measures were defined for evaluation across the 10 proposed scenarios. These measures are based on productivity indicators for warehousing that associate pallet handling with resource utilization.

- **Pallets per hour rate (PHR):** This is calculated as the number of pallets dispatched per unit of time in hours (refer to Eq. (2)).

$$PHR = \frac{SP}{SH}, \tag{2}$$

where

PHR: pallets per hour rate.
SP: shipped pallets.
SH: simulated hours.

- **Percentage of pallets in the queue (PPQ):** to be stored with respect to the total number of pallets received at the LDC (refer to Eq. (3)).

$$PPQ = \frac{PQS}{RP}, \tag{3}$$

where

PPQ: percentage of pallets in the queue.
PQS: pallets in queue for storage.
RP: received pallets

- **Percentage of stored pallets (PSP):** This index calculates the number of stored pallets relative to the total number of pallets received at the LDC (refer to Eq. (4)).

$$PSP = \frac{SP}{RP} \tag{4}$$

where

PSP: percentage of stored pallets
SP: stored pallets.
RP: received pallets.

3.5.5. Pallet traffic

Based on historical data, the volume of pallets received and the request for pallet orders to be shipped was established, as detailed in Table 13.

3.5.6. Loading, unloading, pick-up, placement, and speed of the equipment

The equipment characteristics evaluated in the LDC operations are outlined in Table 14. This includes the capacity of counter-balanced equipment to transport two pallets per trip to the transit zone.

3.5.7. Schedule

The schedules for the LDC simulation model are defined in Table 15.

3.5.8. Restriction of runs

To manage aisle restrictions, we accounted for the circulation network components of the retractable forklift equipment. The capacity of the nodes is restricted to one for aisles lacking alternate access routes and two for aisles with dual access or distinct entry and exit routes.

3.5.9. Model verification and validation

The data validation, ensuring the simulated model accurately reflects the operator system of the real logistics, was conducted using B.L. Welch's method. This approach, developed over the years, provides a means to compare the means of two normal, independent populations, even when variances differ. The number of repetitions for the model can be calculated using Eq. (5). Note that a greater

Table 13
vol of pallets received and dispatched.

Pallets	Per day	Vehicle capacity (pallets)	Hours per day	Arrival frequency (hours per vehicle)
Received	1200	48	24	0.96
Dispatched	1700	36	16	0.34

Table 14
Equipment characteristics.

Type of equipment	Unloading time (min/ pallet)	Loading time (min/ pallet)	Pick-up time (min/ trip)	Placement time (min. per trip)	Speed (m. per min)
Counterbalanced	1.0	NA	1.0	1.0	66
Retractable	NA	2.5	1.5	1.5	66

Table 15
Simulation model schedules.

Placement	Shift 1	Shift 2	Shift 3
Vehicles receipt	06:00 AM a 2:00 PM	02:00 PM a 10:00 PM	02:00 PM a 10:00 PM
Vehicles dispatching	Not applicable		

Table 16
Data for calculating the number of repetitions.

Variables	Values
Average number of runs	34.65
Historical performance measure	36
Variance of tests	22.31
Number of test replications	30
Level of significance	0.05
Distribution value t	1.697

number of repetitions indicates more precise estimation of averages and significance tests [44].

$$n = \frac{\sigma^2 * \left(t_{\alpha,n'-1}\right)^2}{(\overline{x} - C)^2} \tag{5}$$

where

σ^2 : variance of the test.

$(t_{\alpha,n'-1})$: distribution value t (level of significance : 0.05 and number of test replications).

$\overline{x}$: average number of runs.

C : historical performance measure.

In the average run considered in the model, the values indicate the number of pallets dispatched per hour by the forklift, as detailed in Table 16. The performance measure relates to the capacity of the vehicles to dispatch pallets per hour. The model uses a total of 30 replicates and sets a significance value at 0.05.

$$n = \frac{22.31 \times (1.697)^2}{(34.65 - 36)^2}$$

$$n = 35 \text{ repetitions}$$

The analysis concludes that the optimal number of repetitions for the model is 35. Similarly, the run length is determined to ensure model result stabilization, using Tchebycheff's theorem.

The replicate length, calculated using Eq. (6), confirms that the number of observations (n) is sufficiently large to minimize variation between replicates, thereby enhancing the accuracy of the model [45].

$$n = \frac{1}{\propto}\left(\frac{s}{\in}\right)^2, \tag{6}$$

where

Table 17
Data for the calculation of replica length.

Variables	Values
Reject level	0.05
Standard deviation	4.72364667
Rank	0.2

Table 18
Scenarios.

Scenario	Counterbalanced forklift	Retractable forklift
1	1	3
2	1	4
3	1	5
4	1	6
5	1	7
6	2	3
7	2	4
8	2	5
9	2	6
10	2	7

$\propto$: *reject level*.
s : *standard deviation*.
$\in$: *rank*.
An initial run of $n = 30$, with a range of $+/-$ 0, 2 and a level of acceptance of 95 % (refer to Table 17).

$$n = \frac{1}{0.05}\left(\frac{4,7236}{0.2}\right)$$

$$n = 11.156$$

Following the calculation of replicate length, the number of data points for each replicate length (n) is simulated to apply the F distribution. This distribution is utilized to compare variances between the simulated model data and historical data. To validate this approach, the respective hypotheses of the distribution are established.

- H_0 : no significant difference exists between the number of pallets dispatched per

  hour of the historical data and the results obtained in the simulation model.

- H_1 : significant differences between the number of pallets dispatched per

  hour of the historical data and the results obtained in the simulation model.

$$F_{\propto;n-1;n-1} > F_0$$

$$F_{0.05;11,155;11,155\ =\ 1,031} > F_{0\ =\ 0.994}$$

Note: if the F_0 statistic $> F_\propto$, H_0 is rejected; otherwise, it is accepted.
The decision to accept H_0 is based on the observation that the critical value for $F_\propto$ of one tail exceeds F_0. This indicates no significant difference between the number of pallets dispatched per hour in the historical data and the results from the simulation model.

3.6. Model run

3.6.1. Number of scenarios

In determining the alternatives for simulation, various combinations of counterbalanced and retractable forklift numbers were considered, as depicted in Table 18.

4. Results

The results of the model, derived from running replications for each scenario through the simulation software, are presented by performance measure as follows:

4.1. Production runs and analysis

To conduct the 10 proposed scenarios, the predefined performance measures—PHR, PPQ, and PSP—were calculated. For the pallet handling metrics, the warm-up period of the LDC was factored in. The vehicle dispatch commenced when approximately 40 % of its

Table 19
Results by scenario (mobilized pallets).

Scenario	Counterbalance	Retractable	*PHR*	*PPQ*	*PSP*
1	1	3	24.79	55.72	44.27
2	1	4	25.30	55.40	44.59
3	1	5	25.60	55.34	44.65
4	1	6	25.85	55.31	44.68
5	1	7	25.97	55.29	44.70
6	2	3	43.27	14.56	85.43
7	2	4	44.35	13.71	86.28
8	2	5	45.20	12.82	87.17
9	2	6	45.61	12.16	87.83
10	2	7	45.88	11.70	88.29

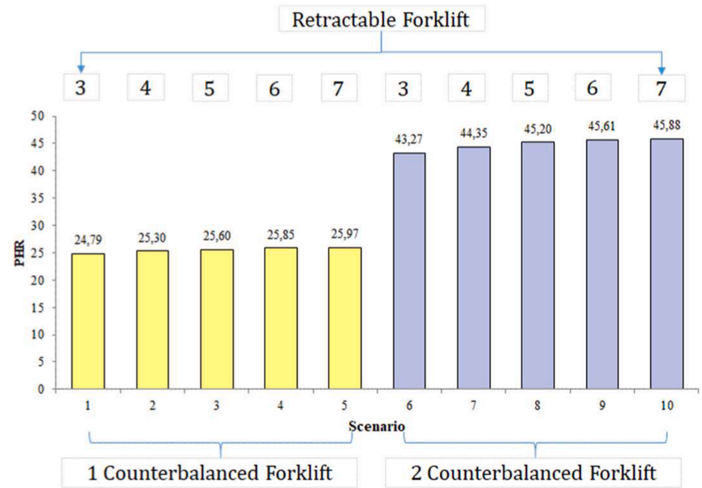

Fig. 7. Pallets dispatched per hour.

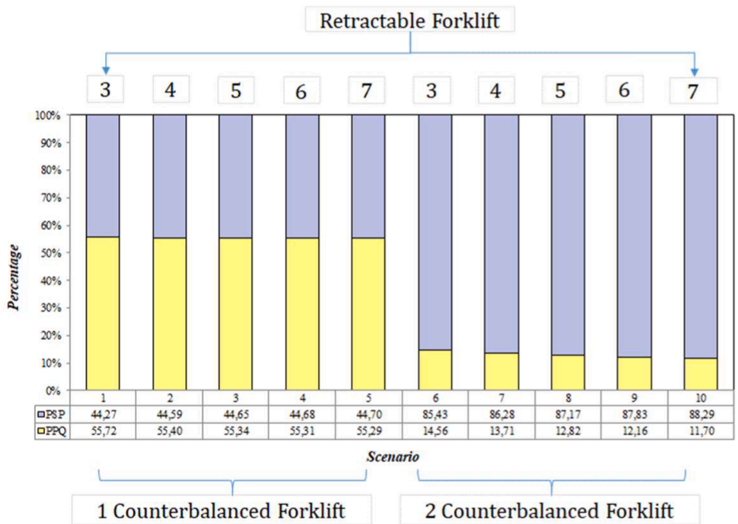

Fig. 8. Percentage of stored pallets concerning pallets in a queue.

Table 20
Results by scenario (equipment utilization and blocking).

Scenario	Counterbalance	Retractable	*PUC*	*PBC*	*PUR*	*PBR*
1	1	3	99.77	0.00	49.19	0.21
2	1	4	99.99	0.00	36.84	0.39
3	1	5	99.99	0.00	29.54	0.48
4	1	6	99.99	0.00	24.59	0.67
5	1	7	99.99	0.00	21.11	0.82
6	2	3	98.73	0.00	95.66	0.25
7	2	4	99.01	0.00	71.92	0.64
8	2	5	99.36	0.00	57.85	5.74
9	2	6	99.71	0.00	48.91	12.12
10	2	7	99.88	0.00	42.47	16.55

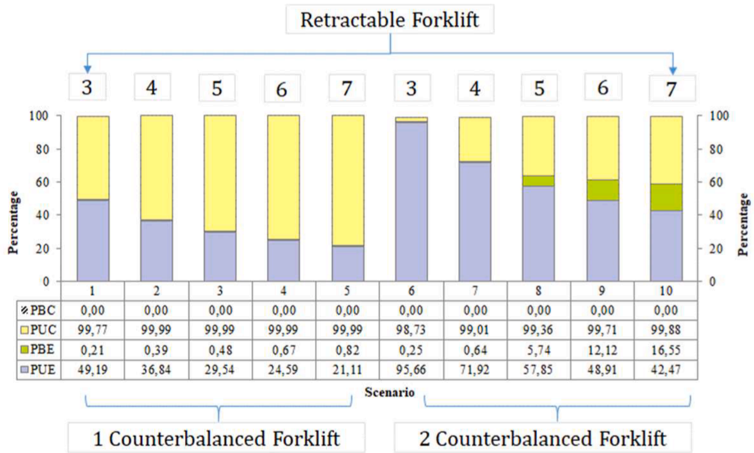

Fig. 9. Percentage of equipment utilization.

capacity was reached, equating to approximately 9456 pallets.

For scenarios 1–5, involving a single counterbalance forklift, the warm-up period was 423 h. In contrast, for scenarios 6–10, which utilized two counterbalance forklifts, the warm-up period was reduced to 216 h. The scenario-specific results related to pallet handling are detailed in Table 19.

4.2. Pallets per hour rate

Considering the average number of pallets dispatched per hour, a notable increase was observed when transitioning from one to two counterbalance forklifts. Interestingly, no significant variations were evident with the addition of more reach trucks, as illustrated in Fig. 7.

4.3. Percentage of stored pallets concerning pallets in a queue

In the subsequent analysis, the results indicated that the average PSP increased proportionally with the addition of counterbalance forklifts—from one to two. Conversely, the average percentage of pallets in queue decreased with the same adjustment in forklift numbers.

Similar to the pallet dispatch rate, the PSP displayed minimal impact from variations in the number of counterbalance forklifts, as depicted in Fig. 8.

Employing simulation to analyze LDC elements yielded initial results for the established performance measures. Among the benefits of simulation is the generation of additional analysis metrics that reinforce the logic of the simulated behavior of the system. The scenario-specific results are demonstrated in terms of the percentage of utilization of counterbalanced forklift equipment (*PUC*), percentage of blocking counterbalance forklift equipment (*PBC*), percentage of utilization of reach truck equipment (*PUR*), and percentage of blocking retractable forklift equipment (*PER*), as detailed in Table 20.

4.4. Use of equipment

In equipment utilization, the counterbalanced forklifts approached 100 % usage, indicating they are a bottleneck in the operation. With an increase in the number of retractable forklifts, the average utilization percentage decreased, whereas the average percentage of blockage owing to aisle restrictions increased, as depicted in Fig. 9.

5. Discussion

DES models for resource allocation in distribution centers offer a heightened level of detail for operations planning compared to alternative methodologies. To effectively compare the outcomes of different methodologies, identical conditions must be simulated under each approach.

A critical component in DES modeling is the data pertaining to the processes being simulated. This is exemplified in the case study by[5], who examined a complex labor allocation system in a warehouse with significant daily workload variability. The study highlighted the need for additional tools to process historical data under such dynamic conditions, necessitating the simulator to sift through irrelevant information and inferentially complete the data for the process being simulated.

Therefore, the selection of simulation methodology becomes a versatile tool, aligning with other research efforts. For instance, [38] utilized DES in customer services to satisfy the service levels of a financial product company. They employed statistical estimations, hypothesis tests, and goodness-of-fit analyses to validate the representativeness of historical data against simulation-derived data.

Differing from existing case studies in literature, this research applied each stage of the DES methodology in a practical manner. Thereafter, statistical tests were used to treat and validate data from each logistic operation, thereby reducing uncertainty and margin of error between historical and simulation-generated data.

The added value of the study lies in its comprehensive simulation of operations in the LDC case study, encompassing activities with similar characteristics. This enables analyses of resource allocation under changing operational conditions. The simulation model facilitates time and cost savings in information gathering and guides the layout design and logistics setup for new clients [38].

In conclusion, the results from models run under various resource allocation scenarios support counterintuitive thinking, rendering them a valuable tool for decision-making. Furthermore, this can impact cost and service levels in logistics operations at LDCs.

6. Conclusions

LR establishes a conceptual trajectory underscoring the significant impact of logistics on organizational performance. Within this framework, the LDC and its internal operations extend beyond mere physical spaces, embodying an environment crucial for satisfying client service level expectations.

The epistemological foundation of this research is supported by variables influencing the problem articulated in the article. It highlights the potential to create analytical scenarios that facilitate understanding the response of the system to alterations in resource allocation and the impact on output percentages across various analyzed elements.

Based on the development of the simulation model of the LDC, we can conclude that with a single counterbalanced forklift, the average number of pallets dispatched per hour is ~26. However, simulations with two counterbalanced forklifts displayed an increase in the average number of pallets dispatched to 45. Despite these variations in the number of counterbalanced forklifts, there are no significant shifts in the average PHR or in the average percentage of pallets stored.

Regarding the other two system performance measures, the results suggest that operating with two counterbalanced forklift trucks positively impacts the average PSP, increasing it from 45 to 87 pallets. Consequently, the average PPQ is expected to decrease from 55 to 13 pallets on average. Notably, these results are not significantly altered by variations in the number of forklift trucks across the 10 scenarios.

The analysis of equipment utilization percentages leads to two key inferences:

(1) Counterbalanced forklifts, regardless of their number, exhibit the highest utilization rate, indicating that the processes they are involved in represent the operation's bottleneck. This bottleneck is influenced by aisle restrictions and available space for this type of forklift.
(2) The use of two counterbalanced forklifts results in an increased number of pallets dispatched per hour and a higher percentage of pallets stored.

Despite their smaller dimensions, retractable forklifts experience a decline in average utilization rate when more units are available. The simulation also reveals an uptick in the average blocking percentage due to aisle constraints in the distribution center, which limits the movement of multiple forklifts in a single operation.

Among the 10 scenarios analyzed, scenario six—which involves the use of two counterbalanced forklifts and three retractable forklifts—demonstrates a noteworthy outcome. This finding signifies an average utilization rate of 98.73 % for counterbalanced forklifts, the highest average utilization rate for retractable forklifts at 95.66 %, and the second-lowest average blocking rate for retractable forklifts at 0.25 %.

The outcomes of the simulation model indicate the following conclusions: employing two counterbalanced forklifts enhances the dispatch rate of pallets per hour. However, given aisle restrictions, the hypothesis that an increased number of forklifts enhances logistics operation performance is disproven.

The analysis by scenarios reveals that a greater number of forklifts correlates with a higher incidence of forklift blockages. Consequently, operation management implement the use of two counterbalanced forklifts and three retractable forklifts.

DES models offer a superior level of detail and specificity in resource allocation within LDC operations, surpassing more generalized methodologies. They enable computational visualization of current and proposed operations under various user-defined scenarios.

The methodology introduced in this paper aims to streamline resource planning in distribution centers through DES models, serving as a blueprint for constructing similar models or even applying it to other types of SC operations.

The primary challenges in this research include accessing information, training teams in DES, and the urgency for rapid results.

Future research for logistics operators should focus on developing DES studies as a tool for informed decision-making regarding resource allocation, facility design, and logistics processes in LDCs, among other aspects.

The fundamental purpose of employing simulation is to identify the most effective strategies for enhancing LDC competitiveness, considering critical factors like time and costs, especially for operations with unique characteristics that necessitate sequential execution, thus adding to the complexity of the system.

Acknowledgements

The authors would like to thank the School of Engineering, Science and Technology of the Universidad del Rosario for its support in the publication process.

Data availability

No data was used for the research described in the article.

Appendix

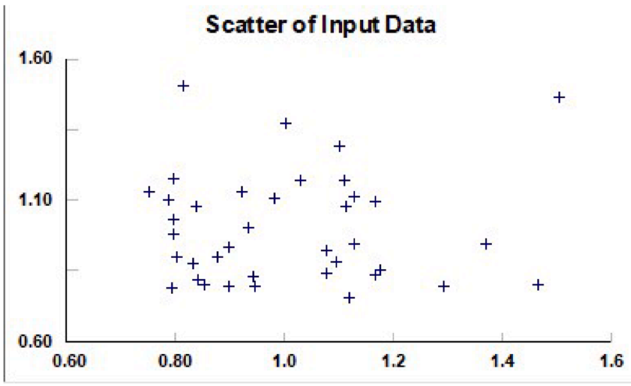

Fig. 10. Independence test for the third variable: time of the placement of a counterbalanced forklift (example).

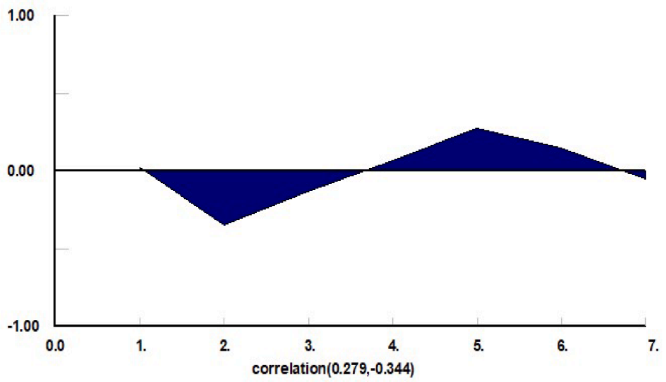

Fig. 11. Autocorrelation of input data for the third variable time of the placement of a counterbalanced forklift (example).

Auto::Fit of Distributions

distribution	rank	acceptance
Johnson SB(0.957, 8.19e-002, -0.106, 0.773)	100	do not reject
Beta(0.954, 1.04, 1.88, 1.5)	91.2	do not reject
Triangular(0.946, 1.04, 1.01)	77.5	do not reject
Weibull(0.801, 10.6, 0.207)	75.8	do not reject
Logistic(1., 1.31e-002)	63.	do not reject
Normal(0.999, 2.17e-002)	59.2	do not reject
Lognormal(-181, 5.2, 1.19e-004)	59.2	do not reject
Power Function(0.954, 1.04, 1.43)	32.2	do not reject
Pearson 5(0.812, 67.2, 12.4)	31.5	do not reject
LogLogistic(0.294, 58.1, 0.705)	31.4	do not reject
Rayleigh(0.951, 3.72e-002)	16.7	do not reject
Uniform(0.954, 1.04)	15.9	do not reject
Extreme Value IB	no fit	reject

Fig. 12. Goodness-of-fit test for location of counterbalanced forklift-distributions ranking (example).

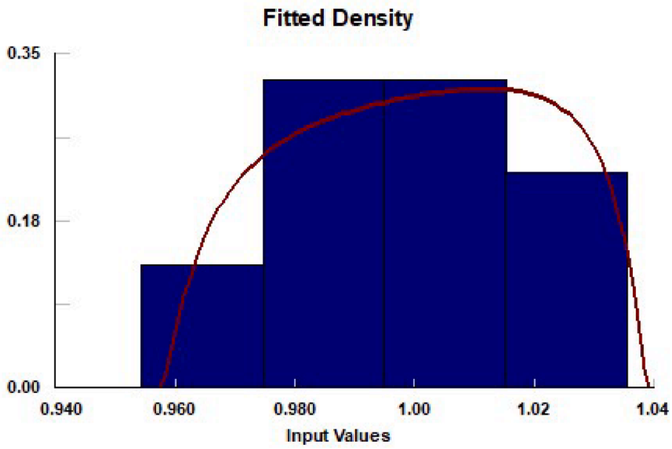

Fig. 13. Goodness-of-fit test for location of counterbalanced forklift-density fit graph (example).

References

[1] A. Calatayud, L. Montes, Logística en América Latina y el Caribe: oportunidades, desafíos y líneas de acción, 2021. https://doi.org/10.18235/0003278.

[2] R. Farromeque, PERLOG LATAM: Perfil Logístico De América Latina, 2017. http://scioteca.caf.com/handle/123456789/1022.

[3] Departamento Nacional de Planeación, National Logistics Survey (2023). https://onl.dnp.gov.co/Documentoscompartidos/DNP_INFORME_V5DIGITAL.pdf.

[4] Consejo Privado de Competitividad, Informe Nacional De Competitividad 2020-2021, 2022. https://compite.com.co/wp-content/uploads/2020/11/web-CPC_INC_2020_2021_LIBRO_DIGITAL_PAGINAS.pdf.

[5] O. Ganbold, K. Kundu, H. Li, W. Zhang, A simulation-based optimization method for warehouse worker assignment, Algorithms. 13 (2020), https://doi.org/10.3390/a13120326.

[6] W. Zhu, J. Liu, Research on Multi-robot Scheduling Algorithm in Intelligent Storage System, J. Phys. Conf. Ser. 1738 (2021), https://doi.org/10.1088/1742-6596/1738/1/012047.

[7] N. Smolic-Rocak, S. Bogdan, Z. Kovacic, T. Petrovic, Time windows based dynamic routing in multi-AGV systems, IEEE Trans. Auto. Sci. Eng. 7 (2010) 151–155, https://doi.org/10.1109/TASE.2009.2016350.

[8] I. Draganjac, D. Miklic, Z. Kovacic, G. Vasiljevic, S. Bogdan, Decentralized control of multi-AGV systems in autonomous warehousing applications, IEEE Trans. Auto.Sci. Eng. 13 (2016) 1433–1447, https://doi.org/10.1109/TASE.2016.2603781.

[9] J. Li, F. Zhang, Z. Wan, J. Sun, L.G. Ke, J. Zuo, K. Li, Design of an optimized forklift routes for a four-door dangerous goods monolayer warehouse through genetic particle swarm optimization algorithm, Internat. J. Indu. Eng. 27 (2020) 276–287, https://doi.org/10.23055/ijietap.2020.27.2.4899.

[10] A.G. Krishna, V.V. Prabhu, Workforce planning models for distribution center operations, in: I. Nääs, O. Vendrametto, J.Mendes Reis, R.F. Gonçalves, M.T. Silva, G. von Cieminski, D. Kiritsis (Eds.), IFIP Adv Inf Commun Technol, Springer International Publishing, Cham, 2016, pp. 206–213, https://doi.org/10.1007/978-3-319-51133-7_25.

[11] J. López, E. Zalama, J. Gómez-García-Bermejo, A simulation and control framework for AGV based transport systems, Simul. Model. Pract. Theory. 116 (2022) 102430, https://doi.org/10.1016/j.simpat.2021.102430.

[12] M. Lucas, T. Skjold, H. Hisken, Computational fluid dynamics simulations of hydrogen releases and vented deflagrations in large enclosures, J. Loss. Prev. Process. Ind. 63 (2020) 103999, https://doi.org/10.1016/j.jlp.2019.103999.

[13] J. Šaderová, D. Marasová, J. Gallikóvá, Simulation as logistic support to handling in the warehouse: case study, TEM J. 7 (2018) 112–117, https://doi.org/10.18421/TEM71-13.

[14] A. Motroni, A. Buffi, P. Nepa, Forklift tracking: industry 4.0 implementation in large-scale warehouses through uwb sensor fusion, Appl. Sci. (Switzerland) (2021) 11, https://doi.org/10.3390/app112210607.
[15] P. Puvanasvaran, Y.S. Teoh, T. Ito, Novel availability and performance ratio for internal transportation and manufacturing processes in job shop company, J. Indus. Eng. Manage. 13 (2020) 1–17, https://doi.org/10.3926/jiem.2755.
[16] R.M. Estanjini, K. Li, I.C. Paschalidis, A least squares temporal difference actor-critic algorithm with applications to warehouse management, Naval Res. Log. 59 (2012) 197–211, https://doi.org/10.1002/nav.21481.
[17] X. Ge, Y. Jin, C. Zhu, Analysis and optimization of forklift truck steering wheel idle vibration, J. Adv. Mech. Design, Sys. Manufact. 9 (2015) JAMDSM0023, https://doi.org/10.1299/jamdsm.2015jamdsm0023. –JAMDSM0023.
[18] M. Frego, P. Bevilacqua, S. Divan, F. Zenatti, L. Palopoli, F. Biral, D. Fontanelli, Minimum Time - Minimum Jerk Optimal Traffic Management for AGVs, IEEe Robot. Autom. Lett. 5 (2020) 5307–5314, https://doi.org/10.1109/LRA.2020.3007435.
[19] A. Faveto, L. Panza, G. Bruno, V. Cirimele, S.S. Furio, F. Lombardi, Efficient management of industrial electric vehicles by means of static and dynamic wireless power transfer systems, Intern. J. Adv. Manuf. Techn. 123 (2022) 1249–1267, https://doi.org/10.1007/s00170-022-10216-0.
[20] A. Burinskiene, The travelling of forklifts in warehouses, Intern. J. Simul. Model. 10 (2011) 204–212, https://doi.org/10.2507/IJSIMM10(4)4.191.
[21] A. Abideen, F.B. Mohamad, Improving the performance of a Malaysian pharmaceutical warehouse supply chain by integrating value stream mapping and discrete event simulation, J. Model. Manage. 16 (2021) 70–102, https://doi.org/10.1108/JM2-07-2019-0159.
[22] H. Ma, K. Wang, Fusion of RSS and phase shift using the kalman filter for RFID tracking, IEEe Sens. J. 17 (2017) 3551–3558, https://doi.org/10.1109/JSEN.2017.2696054.
[23] F. Yener, H.R. Yazgan, Optimal warehouse design: literature review and case study application, Comput. Ind. Eng. 129 (2019) 1–13, https://doi.org/10.1016/j.cie.2019.01.006.
[24] A. Burinskiene, A. Lorenc, T. Lerher, A simulation study for the sustainability and reduction of waste in warehouse logistics, Internat. J. Simul. Modell. 17 (2018) 485–497, https://doi.org/10.2507/IJSIMM17(3)446.
[25] J. Saderova, L. Poplawski, M. Balog, S. Michalkova, M. Cvoliga, Layout design options for warehouse management, Polish J. Manage. Studies 22 (2020) 443–455, https://doi.org/10.17512/pjms.2020.22.2.29.
[26] F. Ballestín, Á. Pérez, S. Quintanilla, A multistage heuristic for storage and retrieval problems in a warehouse with random storage, International Transactions in Operational Research 27 (2020) 1699–1728, https://doi.org/10.1111/itor.12454.
[27] A. Burinskiene, Optimising forklift activities in wide-aisle reference warehouse, Internat. J. Simulation Modell. 14 (2015) 621–632, https://doi.org/10.2507/IJSIMM14(4)5.312.
[28] R. Carli, M. Dotoli, S. Digiesi, F. Facchini, G. Mossa, Sustainable scheduling of material handling activities in labor-intensive warehouses: a decision and control model, Sustainability (Switzerland) (2020) 12, https://doi.org/10.3390/SU12083111.
[29] D. Kezić, I. Vujović, A. Gudelj, Petri net approach of collision prevention supervisor design in port transport system, Promet - Traffic - Traffico 19 (2007) 269–275. https://traffic.fpz.hr/index.php/PROMTT/article/view/961.
[30] R. Stanković, K. Rogić, M. Šafran, Saving Energy by Optimizing Warehouse Dock Door Allocation, Energies. (Basel) (2022) 15, https://doi.org/10.3390/en15165862.
[31] V. Barral, P. Suárez-Casal, C.J. Escudero, J.A. García-Naya, Multi-sensor accurate forklift location and tracking simulation in industrial indoor environments, Electronics (Switzerland) 8 (2019), https://doi.org/10.3390/electronics8101152.
[32] Y. Li, S. Zhu, Integrated Navigation Method of Electric Forklift Based on Improved Ukf Algorithm, INMATEH - Agricul. Eng. 65 (2021) 505–515, https://doi.org/10.35633/INMATEH-65-52.
[33] J. Saderova, A. Rosova, A. Behunova, M. Behun, M. Sofranko, S. Khouri, Case study: the simulation modelling of selected activity in a warehouse operation, Wireless Networks 28 (2022) 431–440, https://doi.org/10.1007/s11276-021-02574-6.
[34] P. Zajac, T. Rozic, Energy consumption of forklift versus standards, effects of their use and expectations, Energy 239 (2022) 122187, https://doi.org/10.1016/j.energy.2021.122187.
[35] Y.F. Khalil, A probabilistic visual-flowcharting-based model for consequence assessment of fire and explosion events involving leaks of flammable gases, J. Loss. Prev. Process. Ind. 50 (2017) 190–204, https://doi.org/10.1016/j.jlp.2017.09.016.
[36] F. Zheng, Y. Lu, M. Fang, L. Li, Conflict model and time window based multi AGF path finding and coordination, in: Proceedings of the 2023 IEEE International Conference on Real-Time Computing and Robotics, RCAR 2023, IEEE, 2023, pp. 408–413, https://doi.org/10.1109/RCAR58764.2023.10250094.
[37] M.J. Jafari, M. Pouyakian, A. khanteymoori, S.M. Hanifi, Development of a framework for dynamic risk assessment of environmental impacts in chemicals warehouse using CFD-BN, Internat. J. Environ. Sci. Techn. 18 (2021) 3189–3204, https://doi.org/10.1007/s13762-020-03040-0.
[38] M. Becerra-Fernández, M.M. Herrera, C. Trejos, O.R. Romero, Resources Allocation in Service Planning Using Discrete-Event Simulation, Ingenieria y Universidad 25 (2021), https://doi.org/10.11144/Javeriana.iued25.rasp.
[39] W.G. Houf, G.H. Evans, I.W. Ekoto, E.G. Merilo, M.A. Groethe, Hydrogen fuel-cell forklift vehicle releases in enclosed spaces, Int. J. Hydrogen. Energy 38 (2013) 8179–8189, https://doi.org/10.1016/j.ijhydene.2012.05.115.
[40] M.J. Schervish, A.M. Law, W.D. Kelton, Simulation Modeling and Analysis, J. Am. Stat. Assoc. 78 (1983) 743, https://doi.org/10.2307/2288169.
[41] J. Trujillo, J. Vallejo, M. Becerra, Methodology call-centers's simulation-study case, Studiositas 5 (2010).
[42] A. Freivalds, B.W. Niebel, Niebel's Methods, Standards, and Work Design, Mcgraw-Hill higher education, 2009. https://books.google.com.co/books?id=Bn1nPgAACAAJ.
[43] International Labour Office, G. Kanawaty, Introduction to Work Study, International Labour Office, 1992. https://hcmindonesia.files.wordpress.com/2012/12/introduction-to-work-study.pdf.
[44] J.C. Romaina, Flores, Estadística experimental, Universidad Privada de Tacna, 2012.
[45] E. Garcia, H. Garcia, L. Cardenas, Simulacion y Analisi de Sistemas Con ProModel, Pearson Educación, 2013. https://books.google.com.co/books?id=VuEfwtFr1QMC.