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Using simulation modelling to support decision-making in warehouse internal logistics

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Abstract
Manufacturing and logistics companies increasingly rely on warehouse automation and data-driven planning; however practical tools for evaluating how structural decisions influence outbound performance remain limited. This paper addresses this gap by developing a discrete-event simulation model of a warehouse system in which forklifts execute pallet transport tasks according to predefined shipment schedules. The model integrates real inventory data, structured storage addressing (alley-bay-level-slot), forklift routing logic and dock-capacity constraints within a unified ProcessFlow architecture. The experimental study focuses on assessing the impact of dock capacity on outbound operational performance. Three scenarios with varying numbers of docks were analysed while maintaining constant order structure, inventory distribution and transport logic. The evaluation is based on two key performance indicators: forklift utilization and average dock occupancy level. Statistical analysis was conducted using multiple replications and 95% confidence intervals to verify the significance of observed differences. The findings confirm that discrete-event simulation provides a robust decision-support tool for analysing structural modifications in warehouse systems and supports data-driven configuration of outbound logistics processes within Industry 4.0 environments.

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1. Introduction

The analysis of complex phenomena and technological processes constitutes a key element of numerous research endeavors, which employ both empirical methods and analytical approaches based on mathematical formalism. In the era of rapid development of information technologies, computer simulation has gained particular significance and is recognized as one of the most effective tools for supporting the analysis and forecasting of complex system behavior (Kikolski, 2017). This technique involves the construction of computer models that replicate selected aspects of real-world systems and the execution of simulation experiments to evaluate their operational performance (Smith, 2003). These models, based on mathematical representations of processes, enable the virtual reproduction of system dynamics under analysis. The primary objective of computer simulation in the context of manufacturing is to achieve the highest possible fidelity in reflecting the functioning of the real production system within a digital environment (Sujová et al., 2023).

Computer simulation is increasingly being adopted as a decision-support tool in complex industrial systems. According to the ESPRIT Simulation in Europe (SiE) working group, the growing use of simulation technologies reflects a broader trend observed across the European continent. These observations are further supported by more recent research findings, which indicate a rising level of simulation based method implementation within the manufacturing sector (Heavey & Ryan, 2006). Numerous scientific publications and conference proceedings address both the general theory of simulation and its specific applications in the design, optimization, and operation of manufacturing systems. A wide range of specialized software tools is now available, enabling the construction of simulation models and the execution of advanced numerical analyses (Kikolski, 2017).

Computer simulation serves as an advanced decision support tool in industrial environments, particularly in the context of designing and optimizing production systems. Its application enables the reduction of risks associated with implementing significant organizational and technological changes in existing manufacturing setups (Kasemset et al., 2023). Once a

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digital simulation model has been developed, it becomes possible to conduct analyses aimed at identifying the key parameters and components of the process (Lee & Yang, 2023). The model reflects the characteristics of the examined system, including its structure, constraints, and operational mechanisms under specified conditions (Daroń, 2022).

The application of computer simulation in industry is inherently interdisciplinary and encompasses a broad range of issues related to production management and internal logistics. In the literature, simulation is employed for analyzing the structure and operation of production systems, optimizing process flows, and planning logistics operations (Danilczuk et al., 2014). Particular attention is given to the use of simulation for designing and evaluating production line configurations, taking into account factors such as performance, workload balancing, and resource allocation (Caiado et al., 2022).

Research literature extensively describes the use of simulation techniques for improving the spatial layout of industrial facilities (Kasemet et al., 2023). Discrete event simulation models are also applied in the context of real - time control of production operations (Koblasa et al., 2020). In addition, simulation tools are used to optimize internal transport systems, enabling the modeling of interactions between logistics components within a virtual environment (Bardzinski et al., 2019). Simulation also supports decision making processes in production planning, for example, through scenario analysis for the manufacturing of prefabricated components (Kohtamäki et al., 2023).

One of the key applications of simulation in manufacturing environments is the identification of potential bottlenecks and areas requiring improvement (Kliment et al., 2022). By replicating real operational conditions in a virtual environment, it becomes possible to accurately pinpoint elements of the technological process that limit system throughput and generate time and economic losses (Lewicki et al., 2024). The analysis of data obtained from simulation experiments allows for drawing conclusions regarding the efficiency of production lines, the degree of utilization of technical and human resources, and the identification of optimization potential across individual stages of the manufacturing process (Kliment et al., 2022).

Within the framework of the Industry 4.0 concept, computer simulation plays a significant role, particularly in connection with the idea of the Digital Twin (Krynke, 2021). The digital counterpart of the production line serves as a starting point for further analyses in the field of industrial process digitalization (Sujová et al., 2023). In this context, the use of simulation is oriented toward enhancing the transparency of the value chain through the integration of modern tools within production system structures. As a result, operational efficiency increases, costs are reduced, and key performance indicators related to sustainability and other critical parameters characteristic of modern manufacturing environments are improved (Lewicki et al., 2024).

2. Literature review

Computer simulation methods are classified according to various criteria, depending on factors such as the purpose of the analysis, the nature of the modeled system, or the type of data being processed. One of the fundamental classification approaches is based on how the passage of time and state transitions within the system are represented. This allows for the distinction of three main simulation modeling paradigms (Łatuszyńska, 2011).

- Discrete Event Simulation (DES) refers to modeling systems in which the state changes only at specific points in time, namely, when defined events occur such as the arrival of a request, completion of an operation, equipment failure, or resource threshold being exceeded. Between these discrete events, the system remains in a steady state. DES is based on managing a future event list sorted by the scheduled time of occurrence, which is implemented through a simulation clock and an event queue mechanism (Ciaușu-Sliwa et al., 2025). This method is widely applied in modeling systems where unit flows, queuing, and resource allocation are essential - such as manufacturing systems, logistics, transportation networks, telecommunications, queuing systems, and selected healthcare processes (Łatuszyńska, 2011).
- Continuous simulation is characterized by the system state changing continuously over time, unlike discrete event approaches. The system's dynamics are typically described by sets of ordinary differential equations (ODEs), less commonly by partial differential equations (PDEs), or by differential - algebraic equations. This paradigm is used in modeling phenomena where flows are continuous, and the analysis of individual units is not critical. Examples include physicochemical processes, fluid and gas dynamics, ecological models, as well as simulations of population dynamics and selected economic phenomena. A notable subclass of this method is System Dynamics (SD), initiated by J.W. Forrester, which focuses on the analysis of strategic and poorly structured problems. It emphasizes the modeling of cause - effect relationships, feedback loops, and time delays in the operation of complex systems (Łatuszyńska, 2011).
- Agent-Based Modeling and Simulation (ABMS / MABS) focuses on modeling a system as a collection of autonomous, interacting units known as agents. Each agent possesses an internal state and a set of behavioral rules that determine its actions and interactions with other agents and the environment. The global, emergent behavior of the system arises from local, micro level interactions. ABMS is particularly useful for modeling complex adaptive systems where heterogeneity and interaction among units are crucial - examples include social sciences (opinion dynamics, rumor spreading), economics (market behavior), biology (ecosystems, tissue development), and epidemiology (Łatuszyńska, 2011).

The selection of an appropriate simulation paradigm is a decision determined by the specific characteristics of the system under analysis and the defined research objectives. Key factors influencing this choice include the nature of state changes (whether they are discrete or continuous), the desired level of model granularity (individual representation vs. aggregated variables), and the types of relationships present in the system. An improper match between modeling method and system characteristics may result in excessive computational load or distorted analytical outcomes. Given that many real-world processes exhibit both discrete and continuous dynamics, there is growing interest in hybrid approaches that integrate multiple paradigms within a single model (Kawa et al., 2016). One example of such integration is the combination of discrete-event simulation (DES) with fuzzy logic for modeling risk assessment systems in high uncertainty domains, such as airport security control. Another emerging direction involves the use of process mining techniques to analyze event log data as a means of supporting the development of simulation models based on actual operational records (Ciaușu-Sliwa et al., 2025).

In addition to the primary classification based on time representation and state transitions, computer simulation methods can also be categorized according to other criteria. One such criterion is the degree of determinism in the model: in deterministic approaches, identical input data always produce the same output, whereas in stochastic models, randomness is represented using pseudorandom number generators. This allows for the inclusion of variability and uncertainty inherent in real-world processes (Sikora et al., 2015).

Another classification aspect involves the treatment of time. Static simulations, such as those used in Monte Carlo methods, focus on analyzing distributions or equilibrium states without explicitly modeling the passage of time. In contrast, dynamic simulations describe changes occurring in the system as a function of time (Mielczarek, 2009).

More complex typologies can also be found in the literature. For example, Barton distinguishes interactive forms of simulation, such as human model interaction, human machine interaction (used, for instance, in flight simulators), and human digital machine interaction, which refer to direct user interaction with a computer based system. Other classifications consider the type of simulated object or the purpose of the analysis, differentiating between physical simulations, procedural simulations, situational simulations (e.g., decision games), and process simulations (Łatuszyńska, 2011).

Against this background, the paradigms of dynamic simulation discrete event, continuous, and hybrid demonstrate significant differences in terms of time representation, level of aggregation, applied mathematical methods, and typical areas of application (Table 1).

The process of executing a simulation project rarely follows a strictly sequential path. Results obtained during the verification, validation, or output data analysis stages often reveal the need to revisit earlier phases of the project - such as supplementing missing data, correcting the conceptual model, or redefining experimental assumptions. This iterative nature of model development highlights the importance of maintaining methodological flexibility and adopting a systematic, critical approach to evaluating model accuracy at each stage of the project life cycle (Samaranayake et al., 2023).

Table 1. Comparison of the main paradigms of dynamic simulation.

Feature	Discrete-Event Simulation (DES)	Continuous Simulation (e.g., System Dynamics - SD)	Agent-Based Modeling and Simulation (ABMS/MABS)
Basic Concept	Modeling the flow of entities through a network of processes and resources	Modeling flows and accumulations using differential equations	Modeling the behavior and interactions of autonomous units (agents)
Time Handling	Simulation clock advances in discrete jumps to the time of the next event	Time progresses continuously or in small fixed increments	Time progresses in discrete steps or continuously
State Changes	Discrete, occurring at event times	Continuous, described by equations	Rule-based, may be discrete or continuous depending on agent logic
Level of Aggregation	Typically operational level, individual entities/resources	Typically strategic/aggregate level, state variables	Micro level, individual agents
Typical Applications	Manufacturing, logistics, healthcare, telecommunications, service systems	Population dynamics, fluid flows, economic, ecological, and strategic models	Social systems, markets, ecology, biology, epidemiology
Strengths	Accurate modeling of operational logic, queues, and resource utilization	Effective modeling of feedback loops and long-term dynamics	Modeling heterogeneity, adaptation, and emergent behaviors
Limitations	May be challenging to apply to continuous or strategic-level systems	Difficulties in modeling detailed operational logic and individual entities	May be computationally intensive; challenges in calibration and validation

High quality input data are fundamental to reliable and useful simulation. Their completeness, accuracy, relevance to the analyzed problem, and appropriate representation of statistical characteristics including variability and uncertainty, often modeled using probability distributions directly impact the validity of the results. The "garbage in, garbage out" principle, meaning that incorrect or insufficient data lead to unreliable outcomes, fully applies in the context of simulation (Pawliszyn, 2022).

In summary, computer simulation plays an increasingly strategic role in improving production systems, enabling the identification of constraints, optimization of resource utilization, and testing of improvement scenarios without interfering with the real operational environment. The integration of simulation tools with Industry 4.0 technologies such as Digital Twins, real-time data analytics, and automated decision-making is becoming the foundation of modern approaches to production management (Ezhova, 2024). In an era of rapid technological change, simulation has become an indispensable tool for designing future - oriented, adaptive, and sustainable manufacturing (Sujová et al., 2023).

3. Experimental

As part of the experimental work, a complete ProcessFlow logic was developed to reproduce the sequential course of warehouse operations, beginning with the initialization of stock, through the retrieval of load units from storage racks, and ending with their delivery to the shipping area. The model integrates input table data, the physical warehouse layout and the behaviour of transport resources, creating a coherent and fully automated order-handling system (Fig. 1). The initialization phase is driven directly by the WarehouseStock table, which defines the location, attributes and quantities of all palletized units present in the system. An excerpt of this dataset is presented in Table 2, illustrating the structure of the input information used to generate pallets and assign them to specific storage slots.

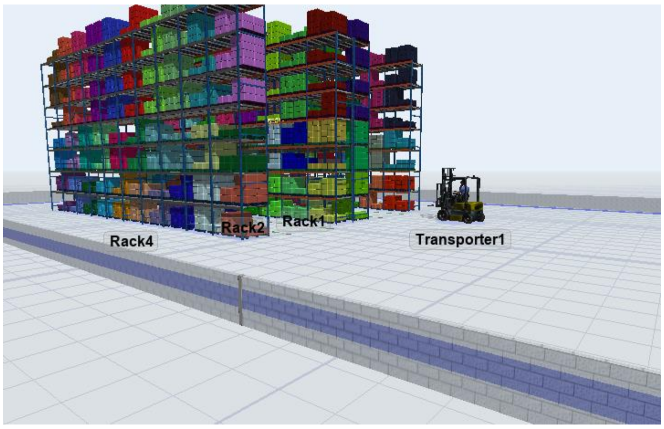

Fig. 1. Simulation model

In the first stage, a module responsible for pallet generation was prepared based on inventory information, ensuring that each unit receives its appropriate attributes and is assigned to the correct storage location in accordance with the warehouse addressing structure (Fig. 2). This section of the logic also handles the creation of pallet content objects and the linking of data stored in the input tables with the physical representation of units in the model.

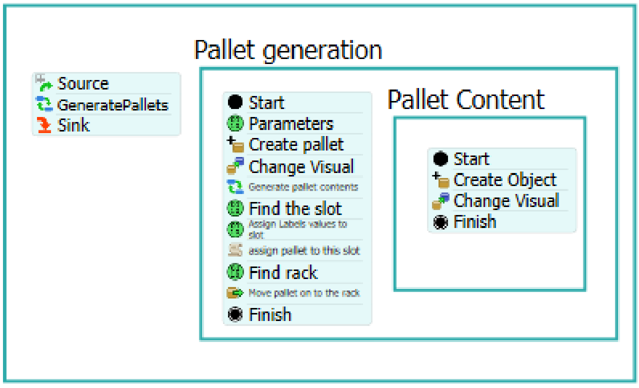

Fig. 2. Pallet generation logic including object creation and location assignment

Within the warehouse initialization module, a dedicated ProcessFlow was implemented to generate pallet objects based on data from the WarehouseStock input table. When a token enters the pallet-generation logic (Fig. 1), the corresponding table record is read and a pallet is created with assigned attributes, including storage address, client, ABC class, product type and stock quantity. These values are stored as token labels and used in subsequent processing stages. The system then generates pallet content according to the specified quantity and identifies the correct storage slot using the recorded address. After locating the appropriate slot within the racking structure, the pallet is linked to the corresponding rack object and placed directly in the 3D warehouse layout. This procedure initializes the system with a fully structured inventory without engaging transport resources. The resulting workflow ensures consistent and repeatable interpretation of input data, providing a reliable starting point for outbound order processing and subsequent simulation stages. The resulting workflow provides an automatic, consistent and fully repeatable interpretation of the input data. Every pallet is created according to the table values, enriched with a complete set of attributes, linked to the correct storage slot and placed into the appropriate rack structure. This establishes a reliable starting point for the outbound order logic and ensures the correct functioning of all subsequent stages of the simulation.

Table 2. Excerpt of the WarehouseStock input data defining pallet locations and attributes.

WarehouseStock

Rack	Bay	Level	Slot	Adress	Client	ABC_Class	Stock_On_Pallet	Product
4	2	6	1	4.2.6.1	Client_4	Class_C	8	C42
4	2	6	2	4.2.6.2	Client_4	Class_C	4	C42
4	2	7	1	4.2.7.1	Client_4	Class_C	4	C42
4	2	7	2	4.2.7.2	Client_4	Class_C	16	C42
4	2	8	1	4.2.8.1	Client_4	Class_C	4	C42
4	2	8	2	4.2.8.2	Client_4	Class_C	4	C42
4	3	1	1	4.3.1.1	Client_4	Class_A	8	A43
4	3	1	2	4.3.1.2	Client_4	Class_A	12	A43
4	3	2	1	4.3.2.1	Client_4	Class_A	16	A43
4	3	2	2	4.3.2.2	Client_4	Class_A	8	A43

A subsequent part of the logic is the module responsible for processing outbound orders, in which pallets belonging to a given order are identified and corresponding transport tasks are generated (Fig. 3). The forklift, directed by the sequence of activities defined in ProcessFlow, executes the retrieval of the required unit, performs the necessary travel operations and completes the task by placing the pallet in the designated dock area. This structure ensures that each operation follows the correct order and that communication between individual components of the model remains consistent.

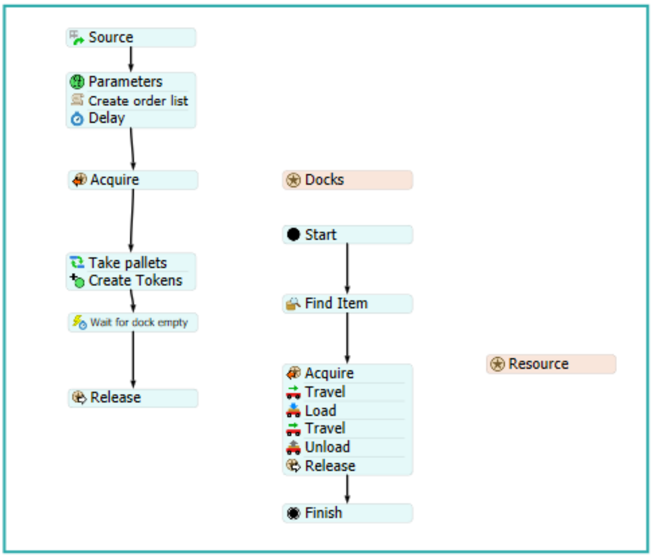

Fig. 3. Order processing logic including pallet identification and the forklift operation sequence

The Order Outbound module manages all operations related to outbound shipment preparation. The process begins in the Source activity, which generates a token for each record in the Order_list table (Fig. 2). The token receives order-specific labels, including the order number and scheduled start time, ensuring that each shipment is processed according to predefined timing. To reflect the planned release moment, the token passes through a Delay activity and waits until the specified start time is reached. The system then dynamically generates a local list of order items by querying the Orders table for records corresponding to the current order number. This subset of data is stored in a token linked table, forming the basis for further outbound operations. Subsequently, a dock resource is acquired to ensure exclusive access during shipment preparation. Once the dock is reserved, the model generates tokens representing individual pallets to be retrieved. The number of generated tokens corresponds to the number of order items, and each token carries the necessary product information to identify the appropriate pallet in the warehouse.

Each generated token initiates a sequence of operations within the Docks subflow. The system first identifies the corresponding pallet based on previously assigned attributes and then activates the forklift operation sequence, which includes resource acquisition, travel to the storage location, pallet loading, transport to the dock, unloading and release of the forklift. This procedure reproduces the complete cycle of outbound pallet handling. After all pallets assigned to an order are processed, the dock is released only when it becomes empty, ensuring proper synchronization of parallel processes and preventing premature resource release. This mechanism guarantees consistent coordination between transport and dock operations. The implemented logic provides an automated and coherent representation of outbound handling, integrating input tables with warehouse objects and transport resources. By controlling order timing, resource allocation and task generation, the model accurately reflects outbound material flow dynamics. The modular ProcessFlow structure enables flexible adjustment of input parameters and testing of alternative configurations without modifying the 3D layout.

To ensure reproducibility and enable quantitative evaluation of system performance, the simulation study was conducted under a clearly defined experimental framework. The model was implemented in FlexSim using the Experimenter module to perform structured scenario analysis. The simulation experiment was conducted over a period of seven consecutive operational days in order to capture system behaviour under extended working conditions and reduce the influence of short-term variability. Each simulated day corresponded to one 8-hour operational shift, resulting in a total simulated time equivalent to seven working shifts.

A warm-up period of 30 minutes was applied at the beginning of each replication in order to eliminate initialization bias resulting from the artificial starting conditions of the system. All performance measurements were collected only after the warm-up period. The extended seven-day horizon ensured that the analysed performance indicators reflect stabilized system dynamics rather than transient start-up effects. The transport routing logic is based on the internal warehouse network, with forklift travel determined by the shortest-path mechanism embedded. Dock allocation follows a resource-acquisition rule ensuring exclusive access to a dock during shipment preparation. Outbound orders are released according to the start times defined in the Order_list table, preserving real operational sequencing and maintaining consistency with the input dataset.

The experimental study was designed to evaluate the impact of dock capacity on the operational efficiency of the warehouse outbound process (Table 3).

Table 3. Summary of experimental scenarios according to dock capacity configuration.

Scenario	Number of docks
Scenario 1	1 dock
Scenario 2	2 docks
Scenario 3	3 docks

All other model parameters remained unchanged across the analysed scenarios, including order structure, inventory distribution, forklift availability and the operational logic of the system. Each scenario was simulated using multiple replications. Statistical analysis was conducted at a 95% confidence level. Mean values, sample standard deviations, minimum and maximum observations, as well as confidence intervals, were computed using the statistical tools available in the Experimenter module. Scenario comparisons were performed using pairwise mean-difference analysis. The designed experimental setup enables the identification of statistically significant differences between alternative dock-capacity configurations.

To evaluate the operational impact of dock capacity, two primary performance indicators were analysed:

1. Forklift utilization (performance level) – defined as the proportion of time during which the forklift was actively engaged in transport operations relative to the total available working time. This indicator reflects the efficiency of transport resource usage and allows identification of potential underutilization or system overload.
2. Average dock content (dock occupancy level) – defined as the average number of pallets present in the dock area during the simulation period. This indicator reflects the degree of material accumulation, the level of congestion, and the potential formation of bottlenecks within the outbound staging area.

For each performance indicator, the following statistical parameters were recorded:

- mean value,
- sample standard deviation,
- minimum and maximum values,
- 95% confidence interval,
- statistical significance of differences between scenarios.

Additionally, a correlation analysis was conducted to examine the relationship between dock occupancy levels and forklift utilization in each analysed scenario. To ensure statistical reliability, all results were evaluated using 95% confidence intervals. The modular structure of the ProcessFlow enabled step-by-step verification of the correctness of individual operational components, including:

- correctness of pallet assignment to storage locations,
- execution of retrieval operations in accordance with the order structure,
- synchronization of dock release logic,
- proper allocation and release of transport resources.

The adopted approach ensures repeatability of results and enables a reliable assessment of the impact of structural changes in warehouse configuration on the operational efficiency of the system.

4. Results and discussion

The results obtained from the simulation confirm that the developed ProcessFlow logic ensures the correct, consistent and fully automated execution of all operations involved in pallet generation, order processing and transport to the docks. The model operated without interruptions, delays or logic conflicts, demonstrating that the integration of input tables, storage structures and transport mechanisms was implemented successfully. Throughout the experiment, every pallet was created according to the information contained in the WarehouseStock table, assigned to the correct storage location and properly translated into physical objects placed within the racking system. This validated the correctness of the initialization module and confirmed that the data-driven approach—linking table values with 3D model behaviour—was functioning as intended.

During order execution, each order was triggered at the planned start time and handled independently based on its dynamically generated list of required pallets. The outbound logic consistently identified the correct items in the storage system, demonstrating the reliability of the coded SQL query and the subsequent transfer of information to tokens. The forklift performed all operational steps in the expected sequence, travelling to the storage slot, loading the pallet, transporting it to the dock and completing the unloading procedure. No errors occurred during the allocation or release of shared resources such as docks or forklifts, confirming that the resource management mechanisms were synchronised and correctly implemented.

A key indicator used to evaluate the operational efficiency of the system was forklift utilization, defined as the proportion of time during which the transport resource was actively engaged in material-handling operations relative to the total available working time. The simulation results revealed a clear relationship between the number of docks and the level of forklift workload. This suggests the presence of significant idle periods resulting from limited dock capacity within the outbound zone. The negligible variability observed between replications confirms the repeatability of the results and the correctness of the implemented resource control logic.

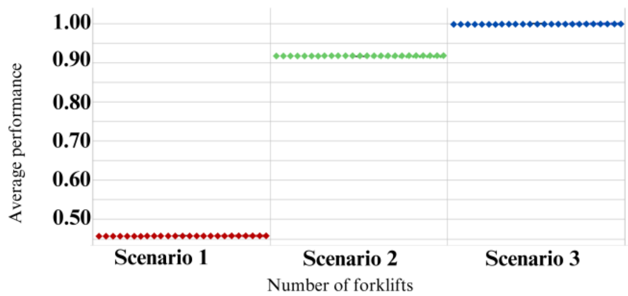

Fig. 4. Average forklift utilization values across the analysed scenarios (S1–S3)

In Scenario S2, the average forklift utilization increased to 0.92, representing more than a twofold increase in workload compared to Scenario S1. Such a substantial change indicates the elimination of the primary operational constraint present in the baseline configuration. In Scenario S3, the indicator reached a value of 1.00 with zero variability across replications, meaning that the forklift operated under full-load conditions throughout the entire analysed simulation horizon.

The summary of descriptive statistics (mean, sample standard deviation, minimum and maximum values, and 95% confidence intervals) confirms the high stability of the model (Table 4). In Scenarios S1 and S2, the standard deviations were practically zero, indicating minimal stochastic variability in system performance. In Scenario S3, a standard deviation equal to zero reflects identical results across all replications, while the absence of a confidence interval results from the deterministic nature of the obtained outcome.

Table 4. Statistical analysis results of forklift utilization depending on the number of docks (S1–S3).

Scenario	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
S1	0.46	0,00	0.46	0,46
S2	0.92	0,00	0.92	0,92
S3	1.00	0,00	1,00	1,00

The comparative analysis of mean differences in forklift utilization relative to the baseline scenario (S1) indicates clear and statistically significant changes following the increase in dock capacity (Table 5). In the case of Scenario S2, the mean difference compared to S1 was 0.46 (95% CI: ± 0.00), while in Scenario S3 the difference reached 0.54 (95% CI: ± 0.00). In both cases, the results were identified as statistically significant, as the confidence intervals for the differences do not include zero.

Table 5. Pairwise comparison of forklift utilization relative to the baseline scenario (S1).

Scenario (j)	Mean difference ($\mu_j - \mu_i$)	95% CI (±)	Statistically significant
S1	–	–	–
S2	0.46	0.00	Yes
S3	0.54	0.00	Yes

The transition from one to two docks results in an increase in forklift utilization of approximately 45.8 percentage points relative to the baseline scenario, whereas increasing the number of docks to three generates an increase of approximately 54.2 percentage points. The extremely narrow confidence intervals indicate minimal variability between replications and high stability of the obtained results. This confirms that the observed differences are not the result of random model fluctuations but rather a direct consequence of the change in infrastructure configuration. It is also noteworthy that the difference between Scenarios S2 and S3 is approximately 0.09, indicating that once the primary bottleneck is eliminated (at two docks), further increases in forklift utilization become substantially smaller. This reflects the phenomenon of diminishing returns and suggests that the system is approaching the saturation level of the transport resource.

The analysis of the average dock occupancy indicator reveals clear differences between the analysed system configurations (Fig. 5).

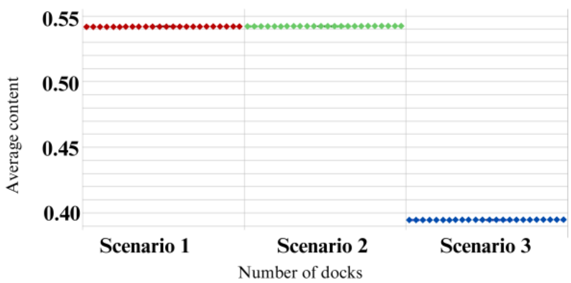

Fig. 5. Comparison of average dock occupancy levels for different dock-capacity configurations (S1–S3).

In the baseline scenario (S1), which includes one dock, the mean value of the indicator was 0.54, with practically zero variability across replications. A very similar value was observed in Scenario S2 (0.54), whereas in Scenario S3 a noticeable decrease in average dock occupancy occurred, reaching approximately 0.40. This indicates that increasing the number of docks to three leads to a substantial reduction in pallet accumulation within the outbound staging area.

The low standard deviation observed across all scenarios confirms the stability of the obtained results and the high repeatability of the model (Table 6). The narrow confidence intervals indicate that variability between replications is negligible, thereby strengthening the reliability of the conclusions.

Table 6. Descriptive statistics of average dock content across analysed scenarios.

Scenario	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
S1	0.54	0.00	0.54	0.54
S2	0.54	0.00	0.54	0.54
S3	0.40	0.00	0.40	0.40

The comparative analysis relative to the baseline scenario (S1) indicates that the difference between S2 and S1 is extremely small (-0.00002), although statistically significant due to the minimal variability in the data. From an operational perspective, however, this difference has no practical relevance, indicating that increasing the number of docks from one to two does not result in a meaningful reduction in the average occupancy level of the outbound staging area.

A markedly different situation is observed in Scenario S3, where the difference relative to S1 amounts to approximately -0.15. The confidence interval for this difference does not include zero, clearly confirming its statistical significance. In operational terms, this corresponds to a reduction in dock occupancy of approximately 14.8 percentage points.

Table 7. Pairwise comparison of average dock content relative to the baseline scenario (S1).

Scenario (j)	Mean difference ($\mu_j - \mu_i$)	95% CI (±)	Statistically significant
S1	–	–	–
S2	- 0.00	0.00	Yes
S3	- 0.15	0.00	Yes

The obtained results demonstrate that increasing the number of docks affects not only the local performance parameters of the outbound zone but also the overall system dynamics. With two docks, the system continues to operate close to its capacity limit, whereas three docks introduce a significant structural change in material flow, reducing pallet accumulation and stabilizing the shipment-handling process.

5. Summary and conclusion

This study developed a data-driven discrete-event simulation model of warehouse outbound operations. The model integrates inventory initialization, structured storage assignment and order processing within a unified ProcessFlow architecture. Operational elements - including pallet attributes, storage locations and transport tasks - are generated directly from input tables, ensuring reproducibility and consistency between data structures and the physical layout.

Two ProcessFlow modules were implemented: one for pallet generation and stock initialization, and another for outbound execution, covering resource allocation, dock management and forklift operations. The modular design ensures synchronized control of events and resources, forming an integrated workflow from data input to shipment dispatch.

The simulation experiments demonstrated stable and deterministic system behaviour across all analysed scenarios. Statistical analysis confirmed significant differences in forklift utilization and dock occupancy depending on dock capacity. Increasing the number of docks substantially improved forklift utilization, while the configuration with three docks reduced dock congestion and shifted the operational bottleneck from infrastructure capacity to the transport resource. These findings highlight the structural interdependencies between dock availability and transport workload.

The model's sensitivity to input data makes it suitable both for performance analysis and for detecting inconsistencies in warehouse databases. Its modular architecture allows easy extension without structural modifications. The proposed approach provides a validated and flexible framework for analysing structural changes in warehouse systems. The results confirm that discrete-event simulation can effectively support data-driven decision-making, enabling the evaluation of infrastructure configurations and the identification of system bottlenecks in a controlled, risk-free environment.

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