PRODUCTION ENGINEERING ARCHIVES 2026, 32(1), 21-33

PRODUCTION ENGINEERING ARCHIVES

ISSN 2353-5156 (print)
ISSN 2353-7779 (online)

Exist since 4th quarter 2013
Available online at https://pea-journal.eu

A simulation model for optimizing component placement in an assembly process

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Article history
Received 30.06.2025
Accepted 12.11.2025
Available online 16.03.2026

Keywords
computer simulation,
optimization,
FlexSim,
assembly components,
internal transport,
process modeling,
resource allocation.

Abstract
This article presents a simulation-based approach to optimizing the placement of components and semi-finished products within an assembly area of a production hall. The developed model focuses on minimizing the total distance traveled by internal transport vehicles – such as AGVs – during the execution of production tasks. A key constraint of the model is the fixed layout of transport routes, which reflects common spatial limitations in real production systems. Therefore, the optimization is limited to the allocation of components in relation to the assembly stations. The simulation model was developed using the FlexSim environment and has a design-oriented character, utilizing hypothetical data. This enables flexible testing of multiple layout scenarios without relying on real-world operational inputs. The proposed approach offers a practical tool for supporting layout planning and internal logistics design in the early phases of manufacturing system development. Additionally, it facilitates comparative analysis of alternative material handling strategies under varying transport capacities and system configurations.

DOI: 10.30657/pea.2026.32.3

1. Introduction

Computer simulation has become one of the key tools supporting the design and optimization of industrial processes, including complex assembly systems. As emphasized by Ulewicz, Czerwińska, Siwiec, and Pacana (2022), a systems-based approach – characteristic of concepts such as lean manufacturing – plays a fundamental role in shaping efficient material flows and production structures, which is increasingly reflected in the application of simulation tools (Ulewicz et al., 2022). In the planning phase of new production systems or during the reorganization of existing assembly halls, the spatial arrangement of components and semi-finished products in relation to workstations becomes particularly important. Suboptimal placement of process elements can lead to longer order fulfillment times, increased internal transport costs, and reduced overall efficiency of material flow (Beaverstock et al., 2017; Krynke & Klimecka-Tatar, 2022).

In contrast to classic warehouse logistics problems – such as inventory placement aimed at reducing picking distances – this study focuses on an assembly layout in which components are delivered to workstations according to a production schedule. While the spatial arrangement of objects may appear similar, the objectives and operational conditions in assembly environments are fundamentally different (Cohen et al., 2019). In warehousing, the priority is on stock availability and turnover; in contrast, in assembly production, emphasis is placed on the continuity of workstation supply and the minimization of unnecessary transport (Tripicchio et al., 2022; Vanko et al., 2023).

The use of simulation environments such as FlexSim enables the modeling of physical layouts of assembly halls, material flow analysis, and system behavior evaluation under various component placement scenarios. This allows decision-makers to test layout configurations without incurring the costs associated with physical modifications. Such models support informed design decisions even before production is launched, offering insights into the impact of component placement on internal transport efficiency and order fulfillment time (Pawlak, 2025; Poloczek & Oleksiak, 2023).

This article presents a simulation model developed to optimize the location of components and semi-finished products relative to assembly stations, assuming a fixed layout of internal transport routes. The primary objective of the model is to minimize the total distance traveled by internal transport vehicles during the execution of assembly tasks. The proposed solution is design-oriented and based on example data, which allows for easy adaptation to various real-world layouts. This approach can be particularly useful during the planning phase of new production facilities or in the modernization of existing assembly lines.

2. Literature review

The application of simulation methods is widely recognized not only in warehouse logistics but also in the design and improvement of manufacturing processes, including assembly operations. In particular, simulation models are frequently employed to plan the spatial arrangement of elements and components within a production facility, ensuring that the supply of parts to assembly workstations is smooth, structured, and as efficient as possible. Simulation enables the realistic representation of production system behavior and supports the analysis of how different organizational scenarios influence process performance and reliability (Daroń, 2022; Krynke, 2023).

As in warehousing, assembly systems require effective control of material and component flow. However, the focus is not on long-term inventory storage, but rather on the just-in-time delivery of parts to the workstations in alignment with production rhythms and spatial constraints. Proper placement of semi-finished products and materials around the assembly line can significantly reduce the time required for auxiliary operations such as internal transport, part picking, or workstation changeovers.

Among the most critical organizational tasks in an assembly environment are:

- ensuring continuous supply of components to production stations to prevent downtime and delays in order execution,
- organizing the workspace to maximize the efficient use of available resources (e.g., floor space, transport devices, operator labor),
- optimizing transport routes between delivery zones, buffers, and assembly workstations,
- protecting production components from damage, contamination, or unauthorized access,
- creating local buffers or kitting points to balance variability in delivery and assembly rhythms,
- maintaining ergonomic standards, workplace safety, and environmental requirements associated with component handling.

Integrating these considerations into simulation models allows for a comprehensive approach to analyzing the performance of assembly systems and supports well-informed design decisions regarding the organization of production space.

Effective management of component flow in manufacturing and assembly environments requires the establishment of optimal organizational, technical, and economic conditions to ensure timely material delivery while minimizing storage and internal logistics costs. Maintaining the continuity of production processes is of particular importance, which entails the need to secure the availability of raw materials, semi-finished products, and components while keeping inventory levels as low as possible. Key elements of efficient material management include accurate demand forecasting, inventory holding cost optimization, proper organization of production and storage space, strategic placement of components based on their usage frequency, and effective supervision of personnel responsible for picking and delivery tasks (Depczyński, 2024). Although a considerable body of literature focuses on analytical methods supporting these processes, the application of computer simulation to evaluate transport performance in production and assembly systems remains less explored in certain areas. In particular, relatively few studies have addressed the combined impact of AGV fleet characteristics (such as number and capacity) and layout configuration (random vs. optimized) on transport efficiency under fixed routing constraints (Rao & Adil, 2017; Venkitasubramony & Adil, 2016). This study contributes to this niche by quantifying how these factors interact and by highlighting nonlinear effects such as congestion and interference.

The spatial distribution of components and materials within production and storage areas plays a critical role in the efficiency of both picking and assembly processes (Lee & Murray, 2019). The primary objective is to place the most frequently used components as close as possible to kitting and assembly zones in order to reduce both travel time and the number of internal transport operations. When delivery volumes are precisely matched to demand, the system can be described as a closed transportation problem (CTP), in which total supply equals total demand (Adlakha & Kowalski, 1999; Biswas et al., 2022). Conversely, when the quantity of delivered materials exceeds current demand, the storage area functions as a buffer, and the situation corresponds to an open transportation problem (OTP) (Rath & Gutjahr, 2014; Sainathuni et al., 2014). Modeling such systems with simulation tools enables a deeper understanding of how different logistical strategies affect the overall performance of production and assembly systems, and it supports the optimization of both material flow and resource utilization.

The picking process, although typically associated with warehouse operations, also plays a critical role in production and assembly environments, where the timely availability of a complete component set directly influences the continuity of assembly operations (Shi et al., 2017). Picking constitutes one of the four fundamental warehouse functions, alongside receiving, storage, and shipping. It involves breaking down standardized load units – such as pallets of components – into smaller, item-specific quantities, which are then assembled into new load units tailored for further transport or immediate use in production. In practice, organizations often seek to optimize transport paths by assigning materials to designated storage zones – usually fixed racks or staging areas. This strategy proves most effective when production or order structures exhibit a high degree of repeatability (Félix-Cigalat & Domingo, 2023; Zhuang et al., 2024). In environments characterized by high demand variability, better performance can be achieved by grouping orders according to similar product categories. This enables more efficient navigation through the storage area and shortens the delivery time of components to production stations or assembly zones (Rymarczyk et al., 2024; Suppini et al., 2024).

When the quantity of incoming materials exceeds the sum of current picking or production orders, the warehouse functions as a short-term buffer, and the possibility of applying preassigned storage locations becomes significantly limited. Fixed storage slots are often partially occupied by inventory awaiting consumption, which forces the logistics system to allocate incoming deliveries based on the "first available rack" or "nearest free space" principle. This situation hinders the use of fixed-location strategies and transport route optimization, as the future structure of demand cannot be reliably predicted. Another challenge is the inability to predefine specific picking or assembly paths in advance (Lesch et al., 2023). In such dynamic environments, decision support through classification-based methods – such as ABC analysis (based on inventory value) and XYZ analysis (based on demand stability) – proves particularly useful. These classifications enable grouping of components according to their consumption frequency and demand predictability, allowing for more flexible planning of storage and picking locations, including in simulation contexts. Simulation models make it possible to analyze various location assignment scenarios and assess their impact on the performance of production and assembly processes (Arani et al., 2021; Errasti et al., 2010; Ivanov et al., 2019).

In the management of material flows within production and assembly warehouses, the optimization of picking routes is a key factor influencing operational efficiency. Due to the complexity of the problem and various real-world constraints, heuristic methods are commonly used in practice. These approaches yield suboptimal, yet practically sufficient solutions from an operational standpoint. Among the most frequently applied are: the *return method*, where the operator returns to the starting point after completing the picking sequence; the *S-shape method*, involving systematic movement along predefined aisle patterns; the *largest gap method*, which selects the widest spacing between items to guide route selection; and the *mid-point method*, which divides the warehouse space based on the geometric center of demand (Engels et al., 2024).

However, route optimization must also take into account real operational constraints within the warehouse environment. These include, for example: the possibility of mutual blocking of forklifts or other transport vehicles in narrow aisles; temporary unavailability of items at designated locations due to delivery schedule shifts or inventory record errors; the need for periodic clearance of storage positions to maintain proper stock rotation; and compliance with established prioritization rules. In the latter case, several strategies are applied, with the most common being *FIFO* (First In, First Out) and *LIFO* (Last In, First Out). A less frequently used but highly relevant approach – especially for components with limited shelf life – is *FEFO* (First Expired, First Out), which prioritizes items based on expiration date (Ching et al., 2019; Mendes et al.).

Due to the multi-criteria nature of the problem and the presence of spatial and resource constraints, the selection of an appropriate mathematical model constitutes a critical stage in designing an efficient picking system. Such models – extensively discussed in the literature – allow for the analysis of how different routing scenarios and prioritization strategies affect total order fulfillment time, resource utilization, and the fluidity of warehouse operations (Bolaños Zuñiga et al., 2020; Rahmani Mokarrari et al., 2025).

Another important aspect in this context is the method of item location assignment within the warehouse space. Two fundamental approaches can be distinguished: the *fixed-location method*, in which each product is assigned a specific, permanent location; and the *random (or floating) location method*, which dynamically allocates storage positions based on current availability and operational needs. The choice between these strategies depends on the characteristics of the material flow and the variability of demand within a given production or assembly environment (Waubert de Puiseau et al., 2022; Xu & Ren, 2020).

Both storage location strategies – the fixed-location method and the random-location method – have their respective advantages and limitations, which must be considered in relation to the specific operational profile of a given warehouse system (Kaczmar, 2019). From the perspective of maximizing the use of available storage space, the random-location method is often more efficient. It enables dynamic occupation of free slots, which is particularly advantageous in environments characterized by high delivery variability and rapid inventory turnover. However, its main limitation lies in the need for an advanced Warehouse Management System (WMS) that can support precise item addressing and fast, error-free retrieval within the warehouse structure (Niemczyk, 2010).

In contrast, the fixed-location strategy, despite its lower flexibility in space utilization, simplifies picking operations and increases the predictability of the process. It is especially recommended in warehouses with limited vertical capacity, where it is feasible to assign items to specific, logically arranged storage zones on a long-term basis (Xu & Ren, 2020).

To assess the actual effectiveness of both strategies under dynamically changing operational conditions, a simulation model will be developed. This model will enable comparative analysis of performance indicators, space utilization, and task completion times related to internal transport and picking activities under various storage location policies.

3. Experimental

The objective of the conducted simulation experiment was to compare the efficiency of supplying assembly workstations with components from the warehouse using two different storage location strategies: random placement versus fixed storage zone assignment. The primary evaluation criterion was the minimization of the total distance traveled by forklifts during the execution of internal transport tasks.

Two variants of a simulation model were developed in the FlexSim environment, reflecting the layout of an assembly hall with a designated storage area and multiple assembly stations, as shown in Figure 1:

- *Variant I – Random placement*: Components delivered from the inbound dock are stored in any available location (the *Queue* object configured with the *Send to Port – Random Available Port* function). The lack of fixed

location assignments results in high variability in transport distances between tasks.
- *Variant II – Fixed location placement*: Components are directed to predefined storage zones specified in the global *Deliveries* table. Location assignment is based on inventory turnover data and proximity to specific assembly stations. The port addresses are dynamically adjusted by the optimizer to minimize the travel distances of AGV forklifts.

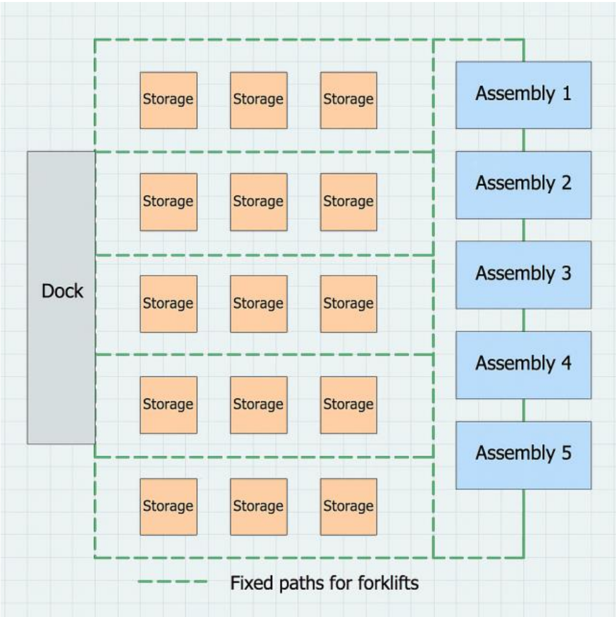


Fig. 1. Layout of the assembly hall with a designated component storage zone, assembly stations, and internal transport routes

To conduct a comparative analysis of two material flow management strategies within an assembly hall, a simulation model was developed to reflect a realistic spatial and functional layout. The model parameters were selected based on typical production conditions, taking into account storage zones, transport paths, and assembly workstations. Key parameters adopted in the model are presented in Table 1.

Table 1. Simulation model parameters

Parameter	Value	Description
Hall area	50 m × 60 m = 3000 m²	Total area designated for storage and assembly operations
Number of load units per delivery	348	Each delivery includes 348 assembly components
Number of storage locations	15	Dedicated temporary storage points for components
Number of deliveries	20	Number of unloading and placement cycles
Number of assembly stations	5	Endpoints where components are delivered
Number of forklifts	1÷3	Internal transport vehicles, each carrying one crate
Component types	15	Groups of components identified by *ItemType* and *Color* attributes
Delivery source	1 inbound dock	Main entry point for external component deliveries

The model assumes the use of fixed transport paths for forklifts, allowing for precise analysis of travel distances and comparison of scenarios in terms of transport load and picking efficiency.

Figure 2 presents a simulation model of the assembly hall developed in the FlexSim environment. It includes a component storage area and five assembly stations. The model represents the complete flow of load units – from the receipt of deliveries, through temporary storage, to the final delivery of components to their designated workstations.

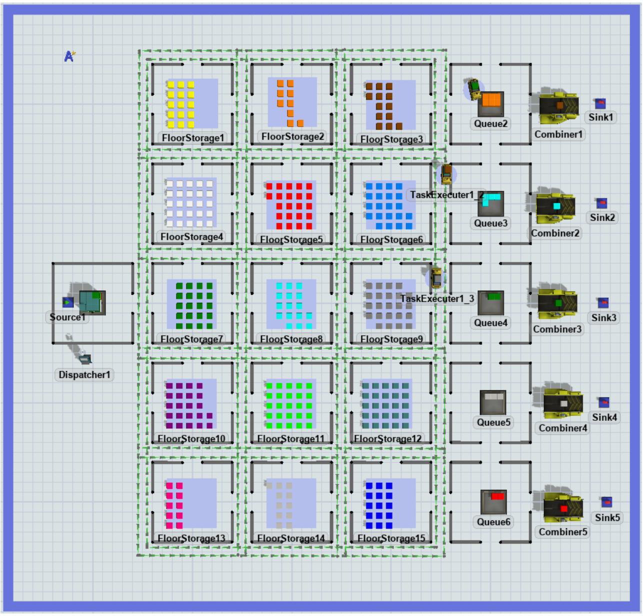


Fig. 2. Simulation model of the assembly hall developed in FlexSim, including the component storage area and the workstation supply system

Deliveries are introduced into the model via the *Source1* object, which generates load units based on a predefined schedule corresponding to the planned delivery timetable. Each unit is assigned attributes such as *itemType* and *Color*, allowing for unambiguous identification and allocation to the appropriate assembly stations (Jurczyk, 2022).

The generated load units are transferred to *Queue1* and distributed across designated storage locations (*FloorStorage1–FloorStorage15*) using AGV vehicles. The exact placement of components depends on the experimental variant being tested and may vary accordingly.

Once the unloading process is complete, the load units are sequentially transported from the storage area to the appropriate assembly stations. This process is carried out automatically and involves the following stages:

- retrieving a component from one of the storage locations (*FloorStorage1–FloorStorage15*),
- delivering it to the queue at a given assembly station (Queue2–Queue6),
- combining the components in the assembly process (*Combiner1–Combiner5*),
- and completing the operation in *Sink1–Sink5*, symbolizing the completion of assembly and consumption of components.

The system operates in continuous mode, with load units generated according to an *Arrival Sequence* schedule (Figure 3).

Arrivals - Source1

Arrivals 20 Labels 2

	ItemName	Quantity	Type	Customer
Arrival1	Product	16	5	1
Arrival2	Product	22	11	2
Arrival3	Product	24	2	3
Arrival4	Product	15	14	4
Arrival5	Product	10	1	5
Arrival6	Product	16	12	1
Arrival7	Product	22	13	2
Arrival8	Product	24	9	3
Arrival9	Product	15	3	4
Arrival10	Product	10	7	5
Arrival11	Product	16	15	1
Arrival12	Product	22	6	2
Arrival13	Product	24	10	3
Arrival14	Product	15	4	4
Arrival15	Product	10	8	5
Arrival16	Product	16	1	1
Arrival17	Product	22	15	2
Arrival18	Product	24	7	3
Arrival19	Product	15	2	4
Arrival20	Product	10	10	5

Fig. 3. Component delivery schedule defined using the Arrival Sequence method in the FlexSim environment

The schedule defines the number of load units assigned to each component type, along with the customer order plan. This allows the model to realistically reflect the demand structure and the requirements of the assembly workstations.

Within the model, two variants of component placement in the storage area can be compared – each developed with the objective of minimizing AGV travel time and maximizing the efficiency of assembly line servicing.

Another essential step in building the simulation model was the creation of a global *Deliveries* table, which specifies the allocation of storage locations (port addresses) used during the unloading of load units (Figure 4).

Deliveries

	Col 1
Row 1	Model.parameters.Parameter1 [1]
Row 2	Model.parameters.Parameter1 [2]
Row 3	Model.parameters.Parameter1 [3]
Row 4	Model.parameters.Parameter1 [4]
Row 5	Model.parameters.Parameter1 [5]
Row 6	Model.parameters.Parameter1 [6]
Row 7	Model.parameters.Parameter1 [7]
Row 8	Model.parameters.Parameter1 [8]
Row 9	Model.parameters.Parameter1 [9]
Row 10	Model.parameters.Parameter1 [10]
Row 11	Model.parameters.Parameter1 [11]
Row 12	Model.parameters.Parameter1 [12]
Row 13	Model.parameters.Parameter1 [13]
Row 14	Model.parameters.Parameter1 [14]
Row 15	Model.parameters.Parameter1 [15]

Fig. 4. Global *Deliveries* table defining the assignment of components to storage locations in the simulation model

This table consists of a single column and fifteen rows, each corresponding to a specific storage location.The table is utilized by the Queue1 object, which serves as a buffer for load units awaiting unloading. In the Output tab of this queue, the operating mode is set to *Send to Port – Using Global Lookup Table* (*Deliveries*), meaning that the routing of units to specific storage locations is based on the values defined in the global table.

During the simulation experiment using the *OptQuest* optimizer, the Deliveries table plays a key role in determining the most efficient component placement strategy. The default values in the table are addresses from 1 to 15, assigned in order corresponding to the numbering of storage locations. However, it may occur that a component with *itemType = 1* is initially assigned to location 1, but in subsequent iterations the optimizer reallocates it to a different location – if that arrangement results in a shorter transport time or better AGV load balancing.

Unlike typical "push" strategies, the applied model utilizes a pull strategy – individual assembly stations (acting as recipients of components) actively request load units with specific labels, stored in the label attribute. In this approach, the label determines both the type and quantity of components to be delivered to each workstation. The *itemType* attribute, on the other hand, is used solely during the unloading stage to route a given component to the appropriate rack in the storage zone.

The optimizer evaluates various component placement combinations by iteratively modifying the addresses in the *Deliveries* table. The objective is to identify a storage configuration that minimizes the total distance traveled by AGVs, thereby maximizing the efficiency of component delivery to the assembly stations.

All storage locations in the model, as well as the inbound buffer, are configured with the Use Transport option. This ensures that the transportation of units is handled by AGVs (*TaskExecuters*), managed by a central *Dispatcher* object. The *Dispatcher* serves as the logistics supervisor, assigning transport tasks and coordinating the movement of units between the storage zone and assembly workstations.

Input variables in FlexSim are defined as optimization parameters. To configure this, a new *Sequence-type parameter* (*Parameter1*) is created and set to a length of 15, corresponding to the 15 storage locations in the model to be optimized for component placement.

The defined Sequence parameter functions as a decision vector – each element represents a specific component type and stores the port number (i.e., location address) to which the load unit should be sent after unloading. In the *Deliveries* global table, each row references a corresponding value from this sequence parameter. As a result, instead of static values (e.g., 1 to 15), the table dynamically utilizes values assigned during the optimization run, enabling the evaluation of different permutations of component placement across the racks (see Fig. 4).

This configuration provides full control over the assignment of storage locations throughout the optimization process. The *OptQuest* optimizer in FlexSim evaluates different permutations of the Sequence parameter values. Since the length of the parameter is 15, this results in 15! = 1,307,674,368,000 possible placement configurations. Such a vast solution space makes it impractical to perform a full combinatorial search. Therefore, heuristic algorithms are used to find near-optimal solutions efficiently (Krenczyk et al., 2018). The ultimate goal is to identify a component placement configuration that minimizes internal transport distances.

It should be noted that the optimization process was carried out separately for each experimental configuration. In particular, for the results presented in Figures 12–14 and Figures 16–18, the OptQuest optimizer simultaneously adjusted two decision variables: the assignment of component locations to layout positions, and the number of AGVs in the system, assuming a fixed transport capacity per vehicle. As a result, these figures display a Pareto-like front of solutions where transport performance depends on the number of AGVs used.

In contrast, the results summarized in Table 3 were obtained using dedicated optimization runs for each fixed configuration of AGV number and capacity. In these cases, only the assignment of component locations was modified by the optimizer, while the number and capacity of AGVs remained constant throughout the optimization. This ensures that comparisons within Table 3 reflect differences due solely to layout configuration, isolating the influence of transport network interactions under identical AGV settings.

4. Results and discussion

4.1. Variant I – Random Placement

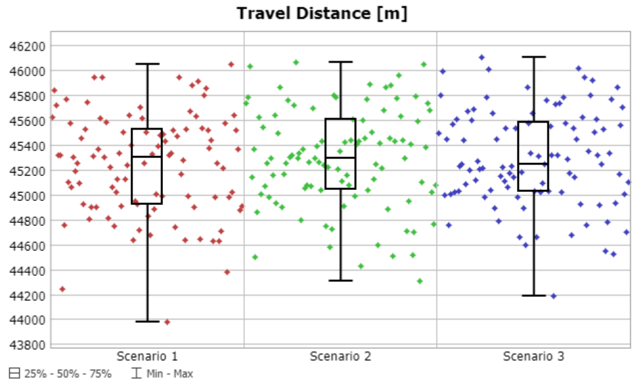
The first analyzed scenario involved a random placement strategy, in which load units arriving at the inbound dock are directed to any currently available storage location. In this variant, components are not assigned to fixed locations, meaning that the distribution of items within the storage zone varies each time and depends solely on real-time availability. This approach results in a random scatter of component locations, which often leads to diverse – and frequently longer – travel paths for the AGV transport vehicles.

Figures 5 through 10 present the simulation results for various scenarios involving different numbers of AGVs (from 1 to 3) and different load capacities (1, 2, and 4 load units per vehicle). The charts illustrate two key performance metrics:

- total distance traveled by all AGVs (Figures 5–7),
- total time required to complete all internal transport operations (Figures 8–10).

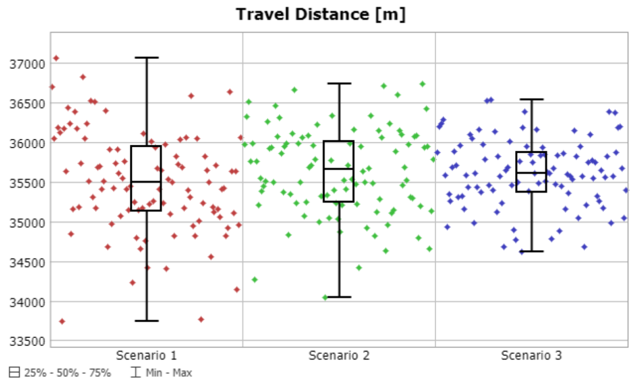
Analysis of the total travel distance reveals that the average cumulative distance remains relatively constant regardless of the number of AGVs used. This indicates that the total number of kilometers traveled by the system as a whole is fairly stable – which is to be expected, given that both the number of transport tasks and the spatial layout of the hall remain unchanged.

Analysis of the charts illustrating the total distance traveled by transport vehicles confirms that the average cumulative distance remains relatively consistent, regardless of the number of AGVs used. This suggests that the total kilometers traveled by the system as a whole remain nearly constant – an expected outcome, as the number of transport tasks and the spatial layout of the facility are fixed.



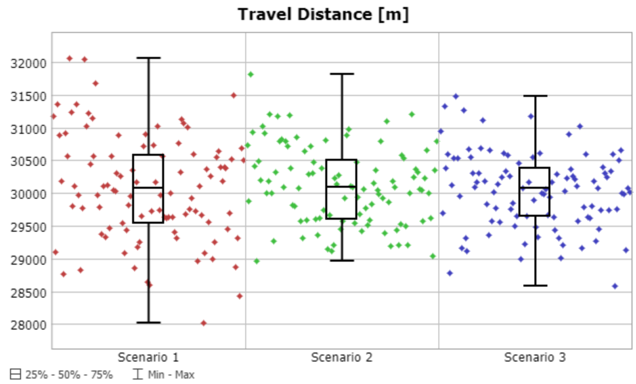
	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
Scenario 1	45242.7 ± 81.2	407.4	43983.3	46048.1
Scenario 2	45292.3 ± 78.8	395.8	44308.3	46065.1
Scenario 3	45293.5 ± 77.3	388.1	44191.1	46100.9

Fig. 5. Total distance traveled by AGV vehicles with load capacity 1: Scenario 1 – 1 AGV, Scenario 2 – 2 AGVs, Scenario 3 – 3 AGVs



	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
Scenario 1	35498.7 ± 127.1	638.1	33748.9	37062.2
Scenario 2	35629.2 ± 109.3	548.7	34040.5	36746.9
Scenario 3	35624.6 ± 85.8	430.5	34615.5	36534.6

Fig. 6. Total distance traveled by AGV vehicles with load capacity 2: Scenario 1 – 1 AGV, Scenario 2 – 2 AGVs, Scenario 3 – 3 AGVs

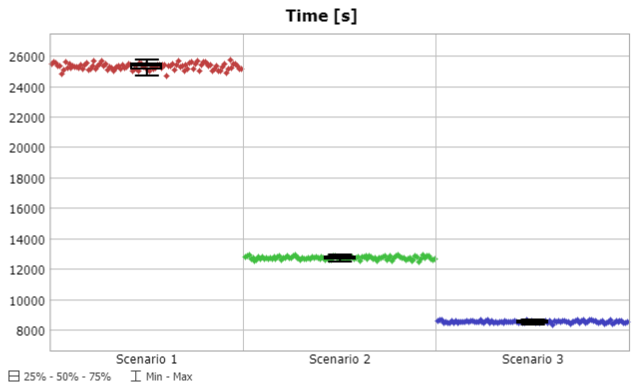


	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
Scenario 1	30078.9 ± 160.5	805.7	28027.5	32056.4
Scenario 2	30117.9 ± 118.2	593.4	28964.5	31812.3
Scenario 3	30039.2 ± 114.8	576.1	28591.0	31488.4

Fig. 7. Total distance traveled by AGV vehicles with load capacity 4: Scenario 1 – 1 AGV, Scenario 2 – 2 AGVs, Scenario 3 – 3 AGVs

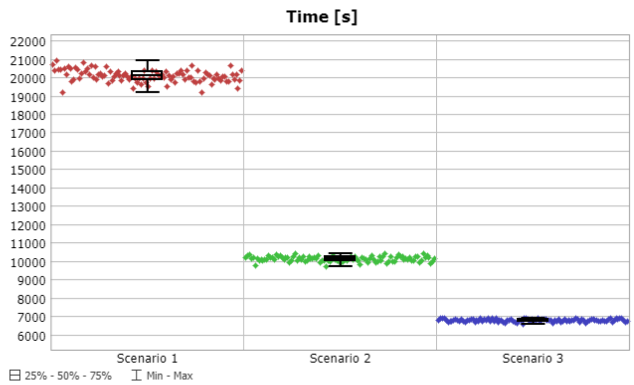
However, a notable difference can be observed in the distribution of results and individual vehicle workload. In single-AGV scenarios, a high degree of variability in travel distances occurs – the vehicle may complete either very short or unusually long routes, depending on the dynamically assigned tasks in each simulation. In contrast, scenarios involving two or three AGVs demonstrate greater operational stability – tasks are more evenly distributed, and the distances traveled by individual vehicles tend to converge toward similar values. Therefore, while the total system distance remains largely unchanged, deploying multiple AGVs reduces outliers and enhances the predictability of transport loads.

Similar to total distance, the transport task completion time also depends on the number of AGVs and their capacity capacities. Increasing the number of vehicles reduces overall time, with the most significant improvement occurring when moving from one to two AGVs. When using three AGVs with high capacity capacity (4 units), the system achieves relatively high time efficiency, although some delays persist due to the unpredictable component distribution.



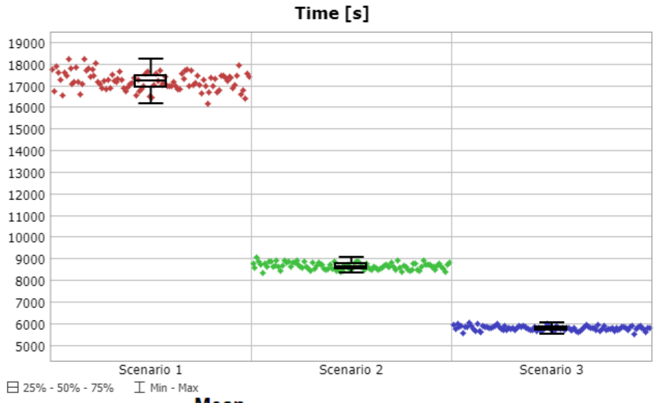
	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
Scenario 1	25305.3 ± 40.7	204.1	24661.8	25711.4
Scenario 2	12749.0 ± 20.1	100.9	12513.6	12956.0
Scenario 3	8560.9 ± 13.3	67.0	8384.2	8700.7

Fig. 8. Total AGV operating time at capacity 1: Scenario 1 – 1 AGV, Scenario 2 – 2 AGVs, Scenario 3 – 3 AGVs



	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
Scenario 1	20090.3 ± 65.9	330.6	19184.1	20899.2
Scenario 2	10131.0 ± 27.9	140.0	9724.6	10433.7
Scenario 3	6792.1 ± 14.7	74.0	6603.4	6932.1

Fig. 9. Total AGV operating time at capacity 2: Scenario 1 – 1 AGV, Scenario 2 – 2 AGVs, Scenario 3 – 3 AGVs



	Mean (95% Confidence Interval)	Sample Std Dev	Min	Max
Scenario 1	17204.5 ± 81.6	409.6	16173.4	18203.0
Scenario 2	8657.3 ± 29.9	149.9	8342.6	9083.5
Scenario 3	5790.6 ± 19.6	98.5	5533.6	6025.2

Fig. 10. Total AGV operating time at capacity 4: Scenario 1 – 1 AGV, Scenario 2 – 2 AGVs, Scenario 3 – 3 AGVs

Key findings for Variant I:

- The absence of fixed location assignments results in low route predictability, which negatively impacts transport efficiency.
- Increasing the number of AGVs and their capacity capacities helps mitigate this effect, but at the cost of higher equipment expenditures.
- A system operating under a random placement strategy is more susceptible to disruptions during peak workload periods.
- The random strategy may be acceptable only in environments with very low transport density or significant resource redundancy.

4.2. Variant II – Fixed-Location Unloading

In the second scenario, load units were assigned to fixed storage locations, as defined by the optimized *Deliveries* table in the FlexSim model. This allowed for deliberate placement of components, taking into account their rotation frequency and intended destination relative to specific assembly stations. The aim of the location assignment optimization was to shorten transport distances and reduce overload on individual AGVs.

The aggregated optimization results are presented in Figure 11 for three levels of AGV capacity capacity: 1, 2, and 4 units. Each section of the chart compares three scenarios: using one, two, and three AGVs, respectively.

Contrary to intuitive expectations, the shortest total transport distance was observed in scenarios involving a single AGV, regardless of its load capacity. As shown in Figures 12 (capacity 1), 13 (capacity 2), and 14 (capacity 4), adding more vehicles to the system did not reduce the overall transport distance in fact, it often resulted in its increase.

This phenomenon can be attributed to vehicle interference effects, such as mutual blocking on shared transport paths, detours caused by congestion, and idle times due to coordination delays.

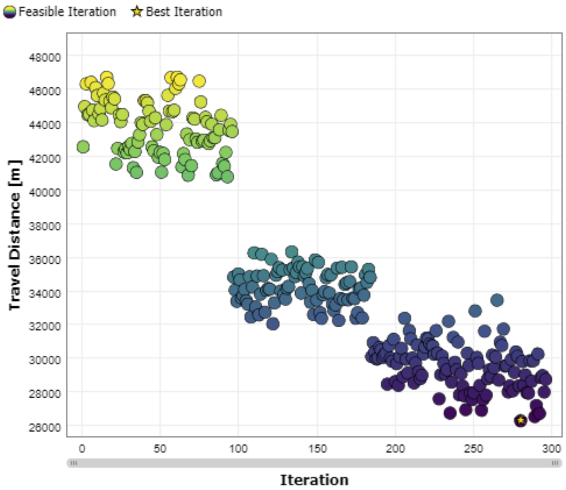


Fig. 11. Aggregated optimization results for minimizing total AGV travel distance (1–3 AGVs) with capacity capacities of 1, 2, and 4 units

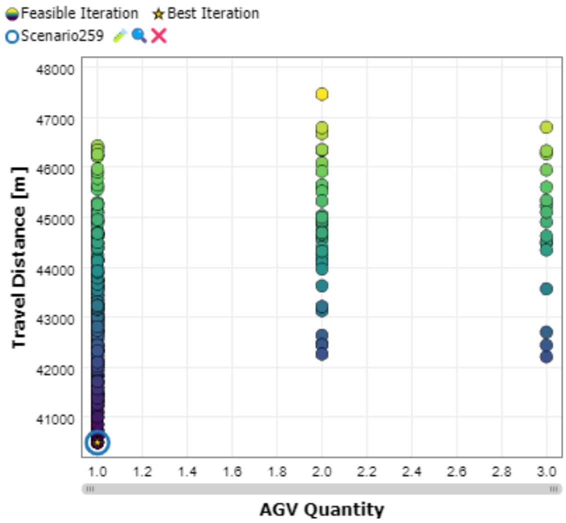


Fig. 12. Total travel distance of AGVs with capacity 1 depending on the number of vehicles used

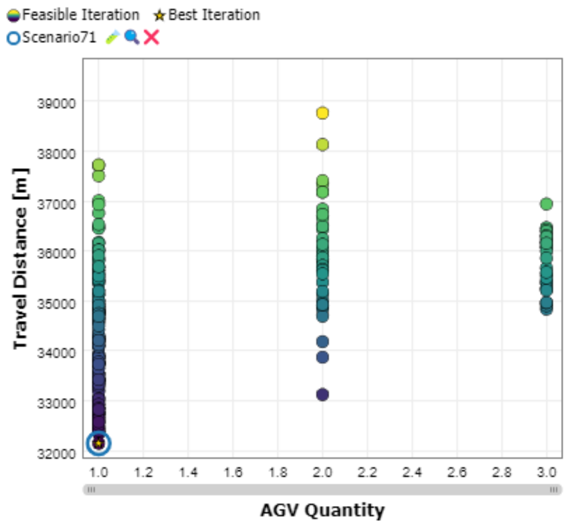


Fig. 13. Total travel distance of AGVs with capacity 2 depending on the number of vehicles used

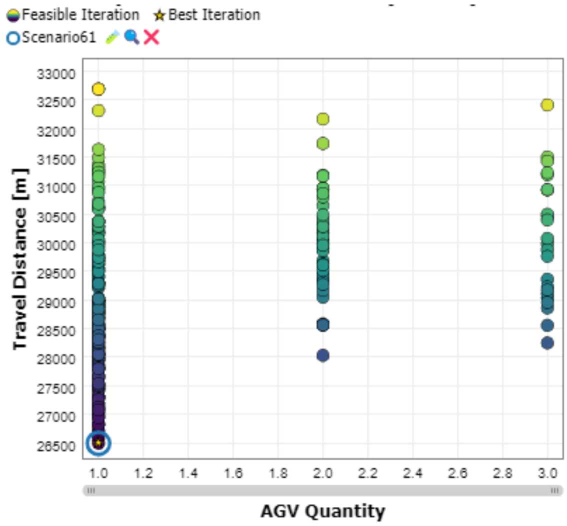


Fig. 14. Total travel distance of AGVs with capacity 4 depending on the number of vehicles used

In single-AGV systems, tasks are executed sequentially, resulting in more orderly and predictable material flow. Introducing a second or third vehicle increases traffic intensity and competition for the same network segments, which may lead to inefficient maneuvers and extended travel paths.

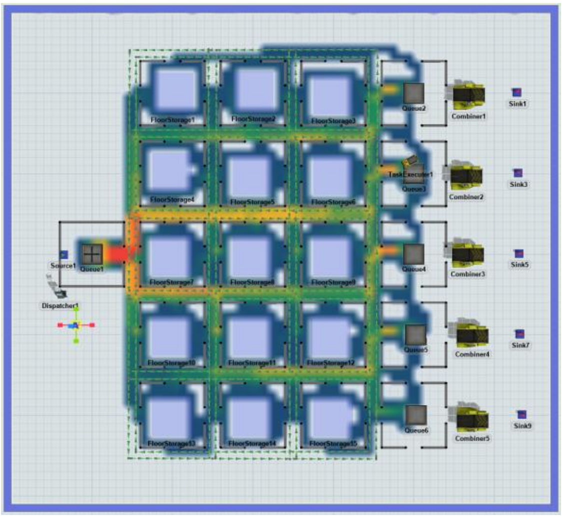
Additional simulation data provide further insight into transport efficiency and the observed inverse relationship between the number of AGVs and the total travel distance. Table 2 presents key disturbance metrics, including the number of route blockages (*waitCount*), total waiting time (*waitTotal*), and the number of route recalculations (*rerouteCount*) for different fleet sizes.

Table 2. Summary of transport interference metrics for scenarios with 1, 2 and 3 AGVs (load capacity = 1 unit)

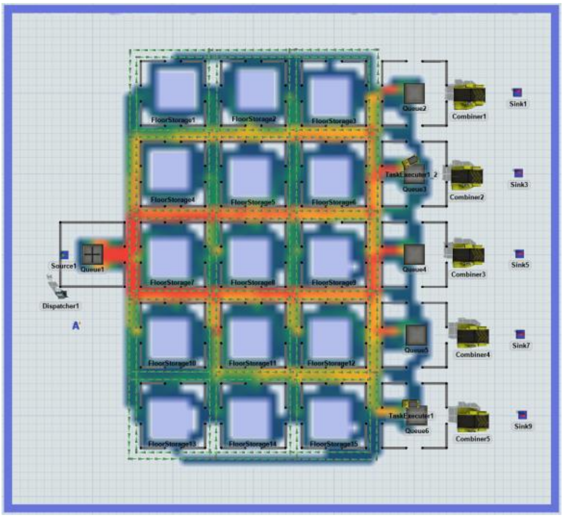
Number of AGVs	Number of Blockages *waitCount*	Maximum Waiting Time *waitMax* [s]	Total Waiting Time *waitTotal* [s]	Number of Reroutes *rerouteCount*
1	0	0	0	2783
2	43	1.68	15.74	1352
	47	1.68	22.34	1449
3	76	1.50	28.53	922
	71	1.68	28.28	965
	73	2.60	34.35	947

The results clearly indicate that the most transport-efficient scenario is the one involving a single AGV. The absence of collisions and route conflicts allows the vehicle to move smoothly, without interruptions or idle time. For this configuration, the simulation recorded *waitCount* = 0 and *waitTotal* = 0.00 s. The corresponding heatmap (Figure 15a) illustrates a uniform utilization of transport lanes, without congestion hotspots.

a)



b)



c)

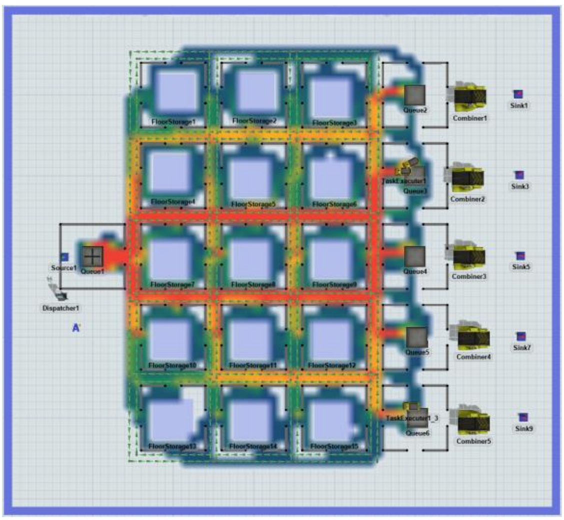


Fig. 15. Heat maps of route utilization for scenarios with 1, 2, and 3 AGVs (load capacity = 1 unit): a) 1 AGV – evenly distributed usage without congestion, b) 2 AGVs – moderate congestion and node interference visible, c) 3 AGVs – significant congestion along central routes and intersections

In contrast, the scenarios involving two and three AGVs experienced 90 and 220 interference events, respectively, with total waiting times of 38.08 s and 91.16 s. Although the value of *rerouteCount* remained relatively constant across all scenarios (~2800), this does not imply effective avoidance of conflicts, but rather reflects repeated local attempts to recalculate paths without successfully alleviating congestion.

At the system level, the number of route recalculations (*rerouteCount*) remains approximately constant in the 1-, 2-, and 3-AGV configurations (2783, 2801, and 2834, respectively). This is likely due to the fixed number of tasks and the way FlexSim handles internal pathfinding computations, which are executed for each task regardless of traffic density. On the other hand, the number of blockages (*waitCount*) and the cumulative waiting time (*waitTotal*) increase significantly with the number of AGVs—from zero in the single-AGV case to 90 and 220 in the two- and three-vehicle scenarios. This suggests that interference, rather than path recalculation, is the primary source of inefficiency in multi-AGV systems.

The heatmaps (Figures 15b and 15c) further confirm the presence of congestion in central lanes and at intersections.

Additionally, in the single-AGV scenario, tasks are executed sequentially, which minimizes the risk of empty return trips and enables more linear and predictable task scheduling. In a multi-AGV system, the absence of centralized task coordination results in an increase in return traffic and competition for shared resources.

It is important to emphasize that the component placement optimizer was tuned specifically for a system with a single AGV operating along predefined paths. When additional vehicles are introduced, these same paths become saturated, and the benefits of the optimized layout gradually diminish. The efficiency of the transport system decreases due to an increasing number of collisions, idle periods, and the loss of flow continuity.

Notably, increasing the number of AGVs does not result in a linear reduction of the total travel distance. On the contrary, the effective transport capacity of the system may be exceeded, leading to a saturation effect. The data presented in Table 2 confirm that beyond a certain number of AGVs, further increases in transport resources yield diminishing, and eventually negative, returns. Figure 16 presents the total task completion time for AGVs with a capacity of 1. In this case, it is clearly visible that using more than one AGV significantly reduces the time required to fulfill transport orders. The system achieves a noticeable efficiency improvement already with two vehicles, while the third AGV further stabilizes the flow of materials.

Figure 17 shows the results for scenarios with AGVs carrying a capacity of 2. Here, the addition of a second AGV leads to a distinct reduction in total operation time, confirming that the system becomes considerably more efficient when using two vehicles instead of one.

The introduction of a third AGV yields only a marginal improvement compared to the two-vehicle configuration. The trend visible in the chart suggests that the system is approaching a point of diminishing returns, where adding more vehicles no longer results in proportional performance gains.

Additional AGVs in this context primarily serve as backup and contribute to the stabilization of task flow.

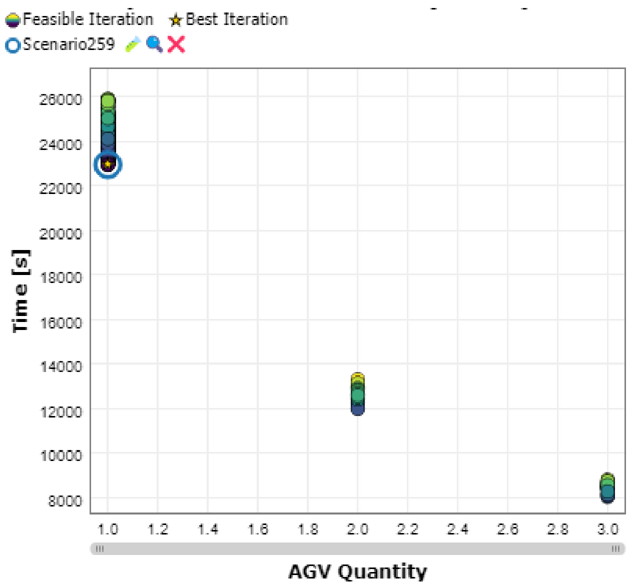


Fig. 16. Total execution time of all transport operations for AGVs with capacity 1 depending on the number of vehicles used

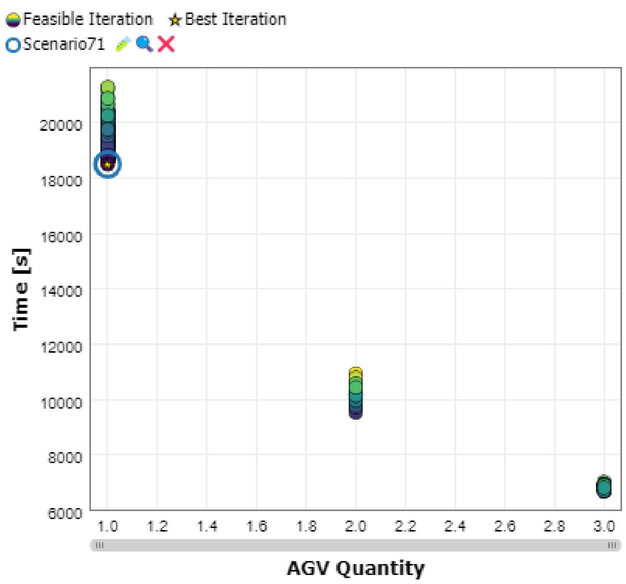


Fig. 17. Total execution time of all transport operations for AGVs with capacity 2 depending on the number of vehicles used

Figure 18, which illustrates the scenario with a capacity of 4, reveals the most effective configuration. Even a single AGV is sufficient to perform most transport tasks within a reasonable timeframe, while the addition of a second AGV further reduces the total operation time. The third AGV does not contribute any significant additional benefit, confirming that with a properly selected capacity capacity, the number of transport resources can be limited without sacrificing performance.

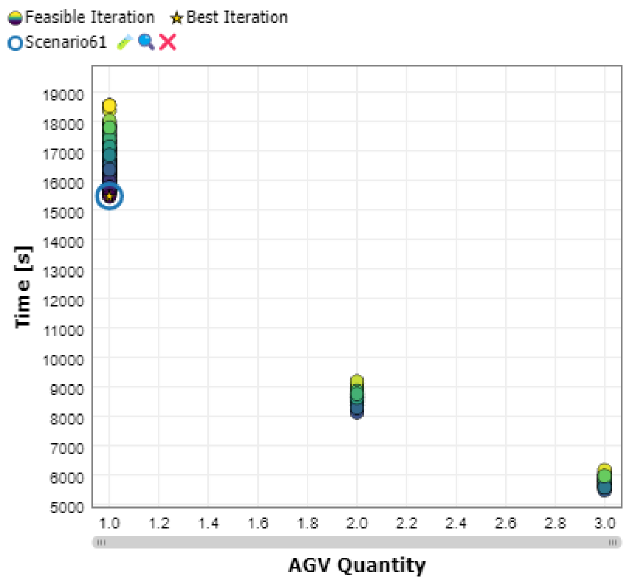


Fig. 18. Total execution time of all transport operations for AGVs with capacity 4 depending on the number of vehicles used

Analysis of Variant II indicates that assigning components to optimal, fixed storage locations results in more balanced AGV workloads and shorter transport paths. The greatest benefits of this strategy are observed with low and medium AGV capacitys, particularly in configurations involving more than one vehicle. AGVs with a higher capacity capacity (4 units) demonstrate greater result stability, regardless of the number of units in operation, making them a particularly attractive solution when designing efficient assembly line supply systems.

In summary, Variant II clearly outperforms Variant I in terms of operation time, transport regularity, and predictability of routes.

4.3. Comparison of Variants

To provide a consolidated comparison of the two analyzed strategies – random unloading of components (Variant I) versus unloading to fixed, optimized locations (Variant II) – the simulation results are summarized in Table 3. Two key performance indicators were compared: the total travel distance covered by AGVs and the total execution time of all transport operations. Additionally, the percentage improvement of Variant II relative to Variant I was calculated for both metrics.

The presented data clearly demonstrate that Variant II outperforms Variant I in all tested scenarios, both in terms of total transport distance and overall system operation time. The most substantial improvements were observed for vehicles with the highest load capacity (4 units), where distance was reduced by up to 13.6%, and operation time by over 11%.

Across all configurations, benefits were also observed when only a single AGV was used, suggesting that well-designed component placement can compensate for equipment limitations and support efficient operation even with a minimal number of vehicles. For load capacities of 1 and 2, the improvements were slightly smaller but still significant, ranging from 6.6% to 10.3% in terms of distance, and from 6.6% to 8.7% in operation time.

Tabela 3. Simulation results for both variants

AGV Count	Capacity	Total Distance [m] Variant I / II	% Reduction (Distance)	Time [s] Variant I / II	% Reduction (Time)
1		45243 / 40784	9.9%	25305 / 23502	7.1%
2	1	45292 / 41778	7.8%	12749 / 11875	6.9%
3		45293 / 41659	8.0%	8561 / 7961	7.0%
1		35499 / 31829	10.3%	20090 / 18337	8.7%
2	2	35629 / 32860	7.8%	10131 / 9464	6.6%
3		35625 / 32715	8.2%	6792 / 6310	7.1%
1		30079 / 26163	13.0%	17204 / 15323	10.9%
2	4	30118 / 26462	12.1%	8657 / 7779	10.1%
3		30039 / 25949	13.6%	5791 / 5151	11.1%

It is also worth noting that the differences between using two and three AGVs were not particularly substantial, supporting the findings from previous subsections, namely, that the system reaches a saturation point beyond which adding more transport units does not yield proportional benefits.

Additional analysis of transport disruptions (Table 2) helps to further explain the differences between the component placement strategies. In the case of random allocation (Variant I), the system was exposed from the outset to a higher number of route conflicts and inefficient travel paths, resulting in longer task completion times and increased resource consumption. In contrast, the optimized layout (Variant II) exhibited significantly improved transport efficiency, but primarily in the single-AGV scenario.

As the number of AGVs increased in Variant II, the benefits of optimization began to diminish. As shown in Table 2, even with two AGVs, the number of route blockages exceeded 90, and the waiting time increased several-fold compared to the single-AGV scenario. With three AGVs, the level of interference and traffic congestion intensified further, as confirmed by the heatmaps in Figure 15.

As a result, although the component placement in Variant II is more logically structured and optimized, its advantage over the random layout (Variant I) diminishes under higher system loads. These findings suggest that the effectiveness of a component allocation strategy depends not only on its inherent quality but also on the level of transport system saturation and the extent of resource sharing between AGVs.

In conclusion, the results clearly confirm that a component unloading strategy based on optimized location assignment not only improves material flow organization in the assembly hall, but also reduces resource usage and shortens order fulfillment time, without requiring investment in additional transport equipment.

4.4. Limitations of the study

The simulation model presented in this study is based on hypothetical and design-time input data. This approach allowed for full control over system parameters, enabling systematic testing of multiple configurations, including combinations of AGV number, capacity, and layout strategy. Such an experimental setup is common in early-stage analysis and provides a valuable foundation for understanding process dynamics and optimization potential.

However, several important limitations should be acknowledged. First, the input data do not reflect real production variability. Factors such as fluctuating demand, delays in task execution, incomplete or imperfect scheduling, and human-related disruptions were not included in the model. As a result, the conclusions, while internally valid, are based on a simplified and idealized view of the system.

Second, the behavior of AGVs was modeled deterministically, without considering random failures, charging cycles, maintenance windows, or deviations from assigned paths due to unforeseen events. This may lead to an underestimation of real-world inefficiencies or routing conflicts.

Third, the simulation assumes perfect system availability and consistent throughput. In practical implementations, variations in supply chain deliveries, operator efficiency, or layout constraints (e.g., blocked zones, maintenance corridors) may alter transport times and AGV interactions significantly.

Another limitation relates to the static nature of demand patterns assumed in the model. The delivery schedules used in the simulations were fixed and uniform, which does not reflect realistic fluctuations over time, such as variable task arrival rates, shift-based production cycles, or urgent replenishment requests. Furthermore, component demand was assumed to be evenly distributed, while in many real systems it follows a strongly polarized structure, e.g., as characterized by ABC analysis. Components with high turnover (A-class) may benefit more from proximity-based layout optimization, while infrequently used parts (C-class) can tolerate longer transport paths. These effects were not modeled in this study but could significantly affect layout efficiency and AGV utilization.

Despite these limitations, the structure of the model allows for future extension and calibration. The simulation framework can be adapted to real-world data, for example by integrating historical production logs or using live monitoring of AGV behavior. Future research should focus on validating the model in an industrial environment, including the effects of scheduling policies, buffer dynamics, and multi-objective trade-offs such as energy consumption, utilization, and delivery punctuality.

5. Summary and conclusion

The objective of this article was to develop and analyze a simulation model of an assembly hall, enabling the comparison of two alternative strategies for component placement within the storage area: a variant based on random location assignment, and one based on fixed, optimized storage locations. The primary goal was to examine how the organization of unloading and component distribution affects the total travel distance of transport vehicles and the execution time of internal logistics operations supporting assembly stations.

The model, developed in the FlexSim environment, was design-oriented and based on sample data, which allowed for the testing of various layout scenarios in controlled conditions without the need for access to a real production system. The simulated hall included one inbound dock, fifteen storage locations, and five assembly stations connected by a fixed network of transport paths.

Variant I, in which components were randomly placed in any available location, proved to be clearly less efficient. While the total travel distance remained relatively stable, there were significant fluctuations in individual route lengths, resulting in poor predictability and uneven workload distribution among AGVs. Furthermore, with an increased number of vehicles, the total distance tended to rise – likely due to vehicle interference, route overlap, and logical collisions within the shared transport network.

Variant II, assuming the allocation of load units to optimized storage locations, demonstrated substantial improvements in both transport distance reduction and overall task completion time. This effect was particularly noticeable for AGVs with high capacity (4 units), where savings reached up to 13.6% in distance and 11.1% in operational time compared to the random variant. It was also observed that with properly selected capacity levels, even a single AGV can maintain a satisfactory level of performance – an important consideration when planning investments in internal logistics infrastructure.

A key finding was the confirmation that excess transport capacity does not necessarily translate into higher efficiency, especially in systems with limited space and fixed movement paths. In many cases, logical optimization – such as better component placement – can yield better results than scaling the system by adding more AGVs.

In conclusion, the developed simulation model has proven to be a valuable design tool for evaluating logistics solutions in an assembly hall environment. The insights gained from the conducted experiments may serve as useful guidelines for designing production layouts and making decisions regarding the spatial organization and supply strategies of assembly stations. The proposed solution can be further developed and adapted to the specific needs of various industrial facilities – whether in the context of new plant design or the optimization of existing manufacturing systems.

It should be noted, however, that the presented results are based on a conceptual simulation model using hypothetical input data and a simplified, static demand profile. In real-world production systems, factors such as variable delivery schedules, differing component turnover rates (e.g., as defined by ABC classification), and planning errors or operational disturbances may significantly affect system performance. Therefore, future work will focus on calibrating the model using real production data and incorporating dynamic demand scenarios. This will allow for more accurate and generalizable conclusions and extend the practical applicability of the proposed simulation approach.

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