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CONTROL, INFORMATICS AND ROBOTICS

A simulation-based comparative study of component allocation strategies in AGV-supported assembly intralogistics

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Abstract. This study addresses the problem of resource management in assembly intralogistics systems integrating human operators and autonomous guided vehicles (AGVs). Despite the growing interest in hybrid intralogistics systems, there is a limited number of studies that simultaneously consider storage allocation strategies, AGV configuration, and human resource involvement within a unified simulation-optimization framework. The objective of this study is to evaluate the effectiveness of alternative component allocation strategies and to support decision-making in hybrid intralogistics systems. A simulation model developed in the FlexSim environment represents a simplified assembly hall including a storage area and assembly stations. Two variants were analyzed: a baseline scenario with random allocation of storage locations and an optimized scenario using a multi-criteria optimization approach implemented with OptQuest. The experiments considered different system configurations, including the number and capacity of AGVs, storage allocation policies, and operator availability. The results show that random allocation leads to significant variability in transport performance and resource utilization, while the optimized variant improves system stability and predictability. The optimization process revealed trade-offs between transport efficiency and operational costs, indicating the need to balance AGV usage and human labor. The findings provide insights into the design and evaluation of hybrid intralogistics systems and highlight the importance of coordinated resource management. At the same time, the study acknowledges its limitations resulting from the use of simplified assumptions and hypothetical data.

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

1. INTRODUCTION

Modern manufacturing companies operate in conditions of increasingly complex logistics processes and high demands for efficiency and flexibility [1, 2]. In contemporary market conditions, the optimization of production and intralogistics processes has become a critical factor for maintaining competitiveness. Companies are required to reduce operational costs, shorten order fulfilment times, and improve resource utilization while maintaining high levels of flexibility and responsiveness to demand variability. There is a growing trend toward integrating traditional work organization methods with modern automation technologies, which is particularly evident in intralogistics, encompassing the transport, storage, and assembly of components within production plants [3, 4]. Autonomous AGV (Automated Guided Vehicles) systems play a key role in this regard, as they reduce internal transport costs, improve safety, and increase process repeatability [5, 6]. At the same time, it should be emphasized that even under conditions of advancing automation, the role of human operators in production organization remains significant. Operators responsible for picking, servicing assembly stations, or supervising processes are an indispensable element of the system, whose effectiveness depends on the proper balance of human and technical resources [7, 8]. Managing such a human-machine hybrid environment requires not only the analysis of technical indicators, such as transport time or route length, but also the assessment of employee workload, utilization, and employment-related costs [9, 10].

In this context, simulation tools that enable the mapping of real production systems and the conduct of experiments under controlled conditions are of particular importance [11, 12]. Digital twin-based solutions are increasingly being developed, allowing simulation to be integrated with current data and better reflecting the dynamics of production systems [13, 14]. Simulation enables the analysis of various organizational scenarios – from variants based on random resource allocation to variants optimized using dedicated algorithms [15, 16]. The literature places increasing emphasis on combining optimization approaches with heuristic ones [17, 18], as well as the practical aspects of picking and storage in facilities [19, 20]. However, existing studies rarely address the simultaneous integration of storage allocation strategies, AGV fleet configuration, and human resource involvement within a single analytical framework. In many cases, these aspects are analyzed separately, which limits the ability to capture their mutual interactions and impact on overall system performance. At the same time, technologies supporting monitoring and localization in intralogistics are

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being developed, such as RFID systems and 3D triangulation algorithms [21].

Such an approach enables the assessment of the impact of the number and load capacity of AGVs, operator staffing levels, and material deployment strategies on flow efficiency, total costs, and system stability [22, 23].

The objective of this study is to evaluate the effectiveness of alternative component allocation strategies and to support decision-making in hybrid intralogistics systems integrating AGVs and human operators. Particular attention is paid to an integrated approach to resource management – both autonomous and human – and to the analysis of the trade-offs between operational efficiency and organizational costs.

The presented research aligns with the principles of Industry 5.0 as defined by the European Commission, emphasizing human-centric and resilient production systems. The integration of autonomous transport systems (AGVs) with operator-supported assembly reflects a balanced automation approach, where technology enhances rather than replaces human labor.

The analyzed production system represents a reference discrete manufacturing environment developed for research purposes. The model reflects a typical multi-variant assembly system characterized by diversified components, decentralized storage areas, and AGV-based internal transport.

Although the analyzed case does not correspond to a specific industrial enterprise, its structural parameters and operational logic are consistent with those of real-world assembly-oriented manufacturing systems, thereby enabling generalizable methodological conclusions.

The use of a generalized industrial configuration allows for the isolation of structural dependencies between layout decisions and transport system parameters without the constraints of company-specific data.

The contribution of this study lies in the integration of storage allocation decisions and AGV fleet configuration within a unified simulation–optimization framework. This approach enables the identification of interdependencies between layout design and transport system parameters, which are often overlooked in traditional sequential planning methods.

2. LITERATURE REVIEW

Discrete Event Simulation (DES) has been widely used for many years in the analysis and optimization of logistics and production processes. Its main advantage is the ability to reflect complex interactions between technical, human, and information resources in a safe experimental environment. The literature indicates that simulation enables both the identification of bottlenecks and the testing of various organizational scenarios without the risk of disruptions in the actual system [2, 24]. DES-based research is applied, inter alia, in production scheduling, material flow analysis, and energy efficiency assessment. It has been pointed out that simulation supports decision-making at the stage of designing and reorganizing production systems [25]. For example, Pawlak *et al*. [25] used simulation models to assess energy consumption in logistics processes, and Breznik *et al*. [8] analyzed the optimization of an assembly line using MTM time standards. Similar conclusions are presented by Zupan and Herakovic [26], who pointed to the role of DES in balancing production lines.

Warehousing and picking processes are also important areas of application. The use of DES in planning picking routes and location allocation strategies has been discussed in numerous publications [20, 27]. Félix-Cigalat and Domingo [28] emphasize that the integration of simulation with the digital twin concept enables the creation of dynamic warehouse models. One of the most widely used tools for DES in logistics and manufacturing is FlexSim. The literature provides both practical manuals [11, 12] and scientific papers using this environment for process modeling [29, 30]. Examples of applications include modeling complex flow systems [31], analyzing the operation of complex machine complexes [32], and planning production logistics [33].

FlexSim simulations have also been widely used in intralogistics process research, for example, to optimize material flows in cell production systems [34] or to evaluate the performance of operators and machines in hybrid systems [7]. Huihui *et al*. [35] also presented an approach to warehouse optimization based on FlexSim, emphasizing its flexibility in scenario analysis. An important area of research concerns issues related to resource allocation optimization, location assignment, and completion problems. These issues can be situated within the broader context of transport theory [36]. Various optimization approaches are used in the literature, ranging from mathematical programming methods [3] to machine learning techniques such as deep reinforcement learning [16] and evolutionary algorithms [36].

Particular attention is paid to dynamic strategies for assigning locations and picking routes [23, 37]. The issue of warehousing in the context of the interaction between storage policy and picking routes has also been widely analyzed [4, 38]. Internal transport involving AGVs (Automated Guided Vehicles) is a rapidly developing area of research. The literature indicates that appropriate route planning and task allocation strategies are crucial to system efficiency [6]. Lee and Murray [5] draw attention to the need to adapt warehouse layouts to the requirements of transport robots, while Cohen *et al*. [1] place the development of such technologies in the broader context of the Assembly 4.0 concept.

Recent studies further confirm the growing importance of simulation and optimization in modern intralogistics systems. Current research has increasingly focused on practical warehouse routing and storage assignment problems [19, 20, 23, 27], as well as on the integration of simulation with energy efficiency and production planning aspects [22, 25]. At the same time, recent developments in AGV scheduling and control optimization indicate that internal transport performance remains an active and dynamically evolving research area [6].

Research also focuses on the interaction between robots and human operators. Barosz *et al*. [7] show the importance of integrating human and technical resources into assembly systems. A similar approach is presented by Krenczyk *et al*. [39], pointing to the effectiveness of hybrid methods in balancing assembly lines.

The development of the digital twin concept opens new possibilities for the simulation and optimization of intralogistics. Rigó *et al.* [14] point to the potential of digital twins in improving the sustainability of logistics processes, while Suppini *et al.* [40] emphasize the importance of sensitivity analysis in order fulfilment processes. The literature also addresses issues related to sustainable development and energy efficiency. Depczyński [41] analyses raw material management using multi-criteria methods, while Pawlak *et al.* [22] focus on energy consumption in logistics.

An important complement to simulation research is the organizational and human perspective. Ulewicz *et al.* [9] argue that the implementation of the lean concept requires both appropriate technical tools and organizational adaptation. Krynke [10] emphasizes the importance of working time management for workstation efficiency, while the works of Kikolski [42] and Gola and Wiechetek [34] demonstrate the potential of simulation for identifying bottlenecks and improving the utilization of human resources. Similar conclusions can be found in studies on sustainable work planning for operators in robotic systems, where the interaction between human workload and system efficiency is also emphasized [7, 8].

Despite the extensive body of literature on simulation, optimization, and intralogistics systems, several limitations can be identified. First, many studies focus on isolated aspects of system design, such as AGV routing, storage allocation, or workforce planning, without considering their mutual interactions. Second, existing approaches often adopt sequential optimization procedures, which do not fully capture the interdependencies between layout decisions and transport system configuration. Third, relatively limited attention has been paid to the combined analysis of technical performance indicators and organizational factors, including human workload and cost-related aspects, within a unified modelling framework.

Therefore, there is a clear need for research that integrates storage allocation strategies, AGV fleet configuration, and human resource management within a single simulation–optimization framework. Addressing this gap enables a more comprehensive evaluation of system performance and supports decision-making in the design of hybrid intralogistics systems.

The integration of people and technology is becoming a key element of modern production and intralogistics systems. The literature review indicates that the development of simulation and optimization methods focuses on three main areas: (1) improving process modeling tools, (2) integrating technical and human resources, and (3) using digital twins and Industry 4.0 concepts.

This study contributes to the existing body of knowledge by providing a unified approach to the analysis of these interdependent factors using a simulation model combined with multi-criteria optimization.

3. RESEARCH BACKGROUND AND METHODOLOGY

This study adopts a simulation-based research approach using discrete event simulation (DES) combined with optimization techniques. This approach was selected due to its ability to model complex interactions between material flow, transport systems, and human resources in a controlled experimental environment.

The FlexSim environment was chosen as the simulation platform because it enables detailed modeling of discrete production systems and allows integration with the OptQuest optimization engine, supporting multi-criteria decision-making. This makes it particularly suitable for analyzing hybrid intralogistics systems where both technical and organizational factors must be considered simultaneously.

3.1. Conceptual framework

The simulation model was developed in the FlexSim environment and represents a simplified assembly hall designed for analyzing material flow and resource utilization (Fig. 1).

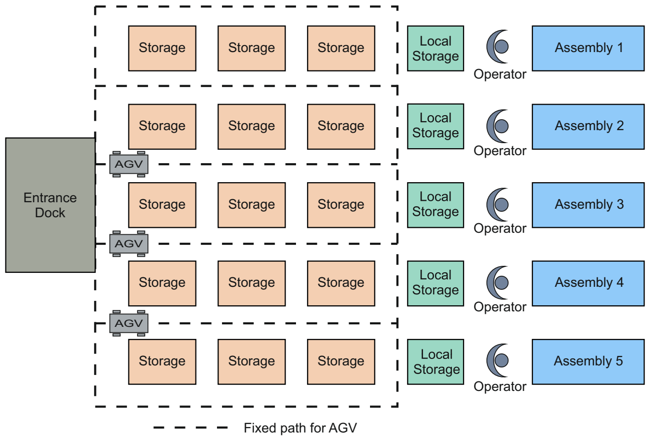


Fig. 1. Layout of the assembly hall with a separate component storage area, assembly stations and internal transport routes

The layout includes an entrance dock, a storage area comprising fifteen distinct storage locations, and five assembly stations connected by a fixed transport network.

The primary means of transport are autonomous AGV trucks, whose number and load capacity were experimental variables. Unlike previous studies [43], the model was extended to include operators working at assembly stations, responsible for transferring components from input queues, preparing batches, and transferring them for further transport. This made it possible to analyze both material flow efficiency and human resource utilization.

To ensure transparency of the analyses, the most important parameters of the model are presented in Table1, while the structure of product manufacturing, considering the types of components, is summarized in Table 2.

The cost values used in the model are expressed in relative cost units, allowing for a consistent comparative analysis of different system configurations rather than representing real financial values specific to a given enterprise.

For the analysis, two unloading variants were defined:

- Variant I – random placement, in which components were placed in the first available location in the storage area.
- Variant II – optimized placement, in which storage locations were assigned according to the global Deliveries table modified by the OptQuest optimizer.

Table 1
Simulation model parameters

Parameter	Value	Description
Hall area	50 m × 60 m = 3000 m^2	Total area designated for storage and assembly.
Number of load units per delivery	348	Each delivery contains 348 assembly components.
Number of storage locations	15	Designated areas for the temporary storage of components.
Assembly station cycle time	1: 940 s, 2: 680 s, 3: 630 s, 4: 1000 s, 5: 1500 s	The duration of a single assembly process at each respective station.
Number of AGVs/capacity	1–3/1–3	Internal transport vehicles, each carrying one to three units.
Component types	15	Groups of components identified by the features: Item, Type, and Color.
Operator labor costs	60 cost units/h	Fixed labor costs for the operators.
Combiner labor costs	Idle: 8 units/h, Processing: 28 units/h, Collecting: 15 units/h	Variable cost assigned according to the operational mode.
AGV utilization costs	Idle: 15 units/h, Travel empty: 30 units/h, Travel loaded: 34 units/h	Variable cost assigned according to the AGV's operational mode.

Based on the presented assumptions, a simulation model was built in the FlexSim environment. Its visualization is presented in Fig. 2, where the storage zone, transport areas, and assembly stations with assigned resources are highlighted.

Table 2
Product production structure

Component quantity	Component type designation	Product type
16	5, 12, 15, 1	1
22	11, 13, 6, 15	2
24	2, 9, 10, 7	3
15	14, 3, 4, 2	4
10	1, 7, 8, 10	5

The analyzed products consist of multi-component assemblies requiring synchronized material supply from distributed storage locations.

3.2. Formal optimization model

To formalize the analyzed problem, a simplified mathematical representation of the system was developed, allowing the identification of key decision variables and performance criteria.

The hybrid intralogistics resource allocation problem analyzed in this study can be formulated as a multi-objective optimization model that integrates spatial assignment decisions with resource configuration variables.

Decision variables

The decision vector consists of:

- $x_{ij} \in \{0, 1\}$ – a binary variable indicating whether component type is assigned to storage location j
- $n_A \in \mathbb{Z}^+$ – the number of AGVs
- $c_A \in \mathbb{Z}^+$ – the load capacity of a single AGV
- $n_O \in \mathbb{Z}^+$ – the number of operators assigned to assembly stations

Objective functions

The problem is formulated as a bi-objective minimization task.

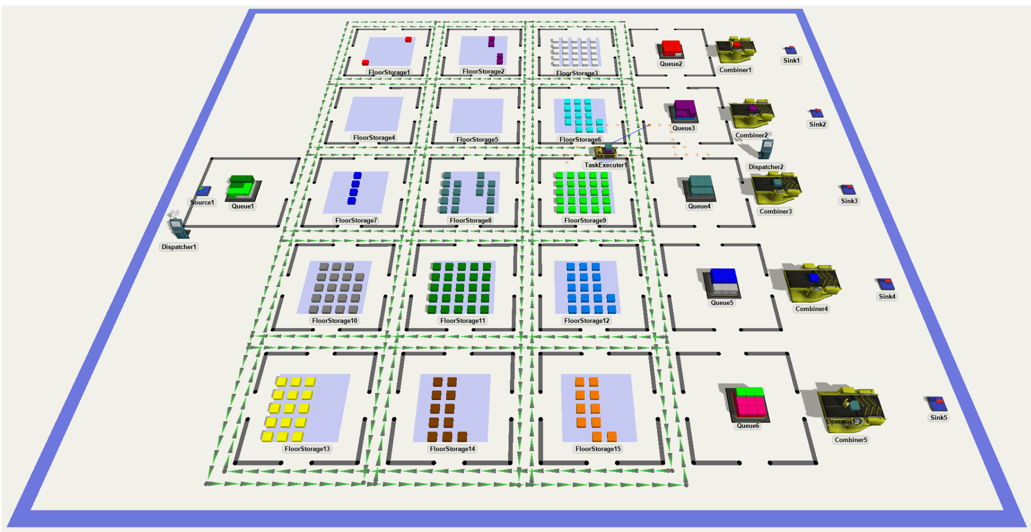


Fig. 2. Three-dimensional visualization of a simulation model in the FlexSim environment

(1) Minimization of total AGV travel distance:

$$\min f_1 = \sum_{k=1}^{n_A} D_k \left(x_{ij}, c_A\right), \tag{1}$$

where D_k denotes the total travel distance of AGV k, dependent on storage allocation and vehicle capacity.

(2) Minimization of total system operating cost:

$$\min f_2 = C_A \left(n_A, c_A\right) + C_O \left(n_O\right) + C_S, \tag{2}$$

where

- C_A – total AGV operating cost (including depreciation and energy consumption)
- C_O – total operator labor cost
- C_S – assembly station operating cost

Constraints

The optimization is subject to the following constraints:

Component assignment constraint:

$$\sum_{i=1}^{m} x_{ij} = 1 \quad \forall i. \tag{3}$$

Each component type must be assigned to exactly one storage location.

Capacity bounds:

$$1 \le n_A \le 3, \tag{4}$$

$$1 \le c_A \le 3, \tag{5}$$

$$1 \le n_O \le 6. \tag{6}$$

Logical feasibility constraints:

- Transport demand must not exceed total AGV transport capacity.
- Assembly processing time must not exceed available operator working time.

The multi-objective nature of the model implies the existence of a Pareto frontier, representing trade-offs between transport efficiency and economic cost. The final selection of the system configuration, therefore, requires the decision-maker's preference articulation or compromise-based analysis.

3.3. Simulation environment

AGV subsystem

In the presented model, an important element of the logistics infrastructure is the internal transport subsystem implemented by autonomous AGV trucks. Their primary function is to transport components from the storage area to the order preparation areas (combiners), from which they are subsequently transferred to the assembly stations.

The transport network has been mapped in the form of fixed paths along which the AGVs move, considering the possibility of collision points and potential blockages when multiple units are operating simultaneously. Each vehicle is equipped with logic modules that enable dynamic route recalculation (rerouting) in situations of overload or network unavailability.

The experimental variants considered different numbers of AGV vehicles (ranging from one to three) and their unit load capacity. These parameters have a significant impact on the organization of transport and the load on individual sections of the network. The study assumed that the AGVs processed transport tasks continuously and that their operation is fully synchronized with the activities of the operators servicing the assembly stations. For each variant, the average working time, distance traveled, and the number of situations disrupting the flow (blockages, downtime, route changes) were determined. These data were used in further economic analysis, where the operating costs of the AGVs were compared with operator labor costs. In this way, the AGV subsystem is not treated solely as a technical element, but also as a component of the entire resource management system, the effectiveness of which affects both the organization of material flow and the operating costs of the company.

Operator subsystem

The second key element of the model is the operator subsystem, which is responsible for component preparation and handling processes. Unlike autonomous AGVs, operators perform manual tasks that constitute an important part of the production process organization and have a direct impact on the smooth flow of materials.

The model assumes that operators are assigned to operate the combiners, whose function is to assemble and mount components. The operators' tasks include:

- Moving components from the input queues to the assembly stations.
- Preparing assembly units and managing the assembly process.

By introducing operators into the model, it was possible to map the actual constraints resulting from the availability of human resources and organization of their work. This enabled the simulation model not only to analyze material flows but also to assess employee workload, their working time, and the occurrence of downtime related to, for example, waiting for an AGV vehicle or the availability of components.

The study defined a variable number of operators assigned to the assembly stations. This made it possible to analyze various organizational scenarios – from minimum staffing levels to variants with surplus personnel. The results obtained allow us to assess the extent to which the availability of operators affects the efficiency of internal transport and the smooth running of the entire production system.

As in the case of AGVs, the activities of operators were linked to economic analysis. Labor costs (hourly rates) were considered and compared with the operating costs of the AGV fleet. This made it possible to compare different system configurations not only in terms of material flow efficiency, but also in terms of organizational and financial costs.

Integrated system configuration

The integrated logistics system in the simulation model combines two subsystems: autonomous AGVs and operators servicing assembly stations. This approach enables the mapping of the interaction between technical and human resources, which are jointly responsible for the material flows in the assembly hall. In practice, the system operates as follows:

- AGVs transport components from the storage area to the production area, delivering them to assembly stations.
- Operators take over the components, complete them in combiners, and handle the assembly.
- Once the operation is completed, the finished batches are transferred to the next stage of production.

The AGVs thus serve as the primary means of internal transport, while operators provide flexibility and quality control in the picking and assembly process. The integration of both subsystems enables the mapping of real-world dependencies, such as:

- Task synchronization: Operators must be available precisely when components are delivered by the AGVs.
- Throughput constraints: The number of available operators impacts the service time of the combiners and can constitute a bottleneck.
- Cost interactions: Increasing the number of AGVs does not necessarily improve efficiency if the number of operators does not increase simultaneously (and vice versa).

This integrated configuration also enables the analysis of organizational variants where the costs of human labor and the operating costs of the AGVs are balanced. This enables the assessment of whether investing in additional autonomous vehicles or employing a greater number of operators is the more profitable solution.

The remainder of the paper will present the simulation scenarios based on this configuration, along with an analysis of their results in the context of the effectiveness of the material flow and the costs of the total system.

3.4. Optimization procedure

The optimization experiments were conducted using the OptQuest engine integrated within the FlexSim simulation environment. Due to the combinatorial nature of the storage assignment problem, heuristic meta-search techniques were employed to efficiently explore the solution space [23].

Search space and decision variables

The key decision variable controlling storage allocation is the Sequence parameter, defining the assignment of 15 component types to storage locations. The number of possible permutations equals: 15! = 1 307 674 368 000.

Such a large combinatorial space makes exhaustive search computationally infeasible. Therefore, metaheuristic optimization is required to identify high-quality near-optimal solutions within reasonable computational effort [19].

Depending on the experimental configuration, the optimizer adjusted:

- Component-to-location assignment (Sequence parameter)
- The number of AGVs in the system

Objective functions

The optimization was formulated as a bi-objective problem with the following objectives:

1. Minimization of total internal transport distance
2. Minimization of total system operating cost

The cost objective includes AGV operating cost and labor-related cost components as defined in Section 3.2.

Optimization settings

Each optimization run was performed with:

- Maximum number of iterations: 500
- Maximum wall-clock time: 200 seconds

The stopping criterion was defined as reaching either the iteration limit or the wall-time threshold.

Experimental configurations

The optimization was conducted separately for each experimental scenario.

In the first set of experiments, the optimizer simultaneously modified the storage assignment and the number of AGVs, assuming fixed transport performance per vehicle. The resulting solutions form Pareto frontiers illustrating trade-offs between transport distance reduction and system cost.

In the second set of experiments, dedicated optimization runs were performed for fixed AGV configurations (constant number and capacity). In these cases, only the storage assignment variable was optimized. This approach isolates the impact of layout configuration from fleet size effects, enabling direct comparison under identical transport conditions.

3.5. Model limitations

The presented simulation model is based on a set of simplifying assumptions that should be considered when interpreting the results. First, the model uses hypothetical data and a generalized production layout, which may not fully reflect the variability and complexity of real industrial environments. Second, the transport network is represented as a fixed path structure, which does not fully capture the capabilities of advanced AGV fleet management systems based on real-time optimization and dynamic task allocation.

Third, the analysis focuses on selected performance indicators, such as transport distance, resource utilization, and operational costs, without including all possible technical and economic factors.

Finally, the optimization process is based on a limited number of iterations and heuristic search methods, which means that the obtained solutions represent near-optimal configurations rather than global optima.

Despite these limitations, the model provides a useful framework for comparative analysis and supports decision-making in the design of hybrid intralogistics systems.

4. RESULTS AND DISCUSSION

The analysis focuses on selected key performance indicators, including total AGV travel distance, total operation time, resource utilization, and total system cost. These indicators were chosen as they directly reflect the efficiency of material flow, the level of resource usage, and the economic performance of the system, which are critical for decision-making in intralogistics design.

4.1. Variant I – random placement

The first scenario analyzed involved a random placement strategy, in which load units delivered to the entrance dock were directed to storage locations designated randomly. The randomization procedure consisted of assigning each component type to a single storage location selected randomly from the available slots. This means that all units of the same type always went to one randomly selected slot, and there was no mixing of different component types within a single location. All results are presented as average values obtained from simulation runs for each scenario.

Figures 3 and 4 present the simulation results for nine experimental scenarios. Scenarios S1–S9 correspond to combinations of the number of AGVs (1–3) and their load capacity (1–3).

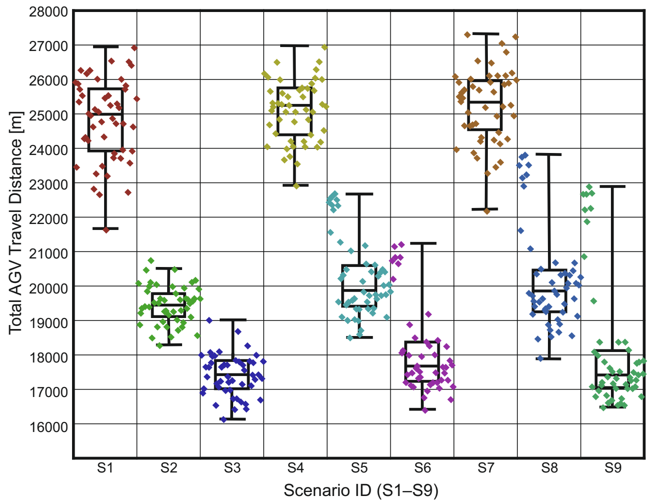


Fig. 3. Total AGV travel distance across experimental scenarios (Variant I – random storage allocation)

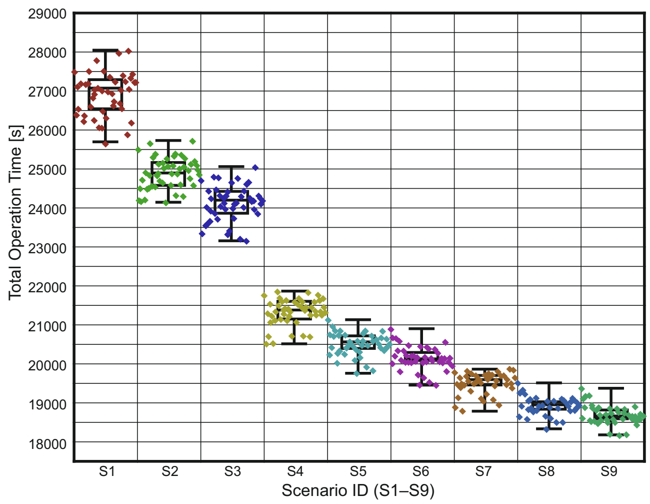


Fig. 4. Total operation time across experimental scenarios (Variant I – random storage allocation)

The scenarios are defined as follows:

- Scenarios S1–S3 correspond to one AGV with increasing capacity (1, 2, and 3).
- Scenarios S4–S6 involve two AGVs with capacities ranging from 1 to 3.
- Scenarios S7–S9 include three AGVs with capacities of one, two, and three units.

The analysis of the distances traveled (Fig. 3) shows clear differences between the configurations. Although the total distance traveled by the system remains relatively stable with a greater number of AGVs, the distribution of results indicates that scenarios with one vehicle show high load variability – a single AGV can cover both shorter and significantly longer routes depending on the dynamics of task assignment. Adding additional AGVs does not reduce the total travel distance of the system but leads to a more even distribution of work among the vehicles and limits extreme load values.

The analysis of the operational time (Fig. 4), on the other hand, shows a clear impact of the number of vehicles. Increasing the number of AGVs leads to a reduction in the time required to complete all transport tasks. The greatest improvement occurs when transitioning from one to two vehicles, while adding a third vehicle yields smaller benefits. The impact of capacity is also noticeable since higher capacity shortens the completion time, but these effects are less pronounced than increasing the size of the fleet.

In addition to classic efficiency indicators, the economic aspect was also included in the analysis. Figure 5 presents the total system costs across the nine scenarios (S1–S9). It can be observed that lower costs do not always correspond to the shortest routes or times; the decisive factor is the relationship between the cost of operator labor and the cost of AGV operation.

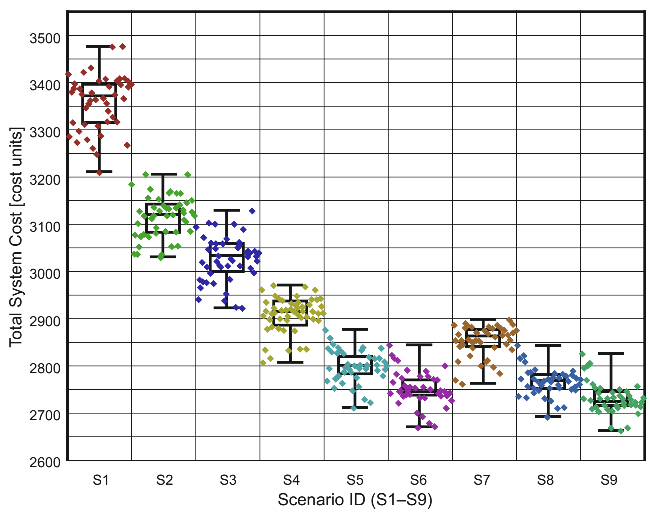


Fig. 5. Total system operating cost across experimental scenarios (Variant I – random storage allocation)

The subsequent results concern resource utilization. Figure 6 presents the average utilization level of the AGV fleet. The utilization values represent the average percentage of time during which a given resource was actively engaged in processing tasks. It is clearly observed that as the number of vehicles increases, their utilization level decreases. This indicates that additional AGV units are not operating at full capacity, which may lead to reduced cost-effectiveness of the system.

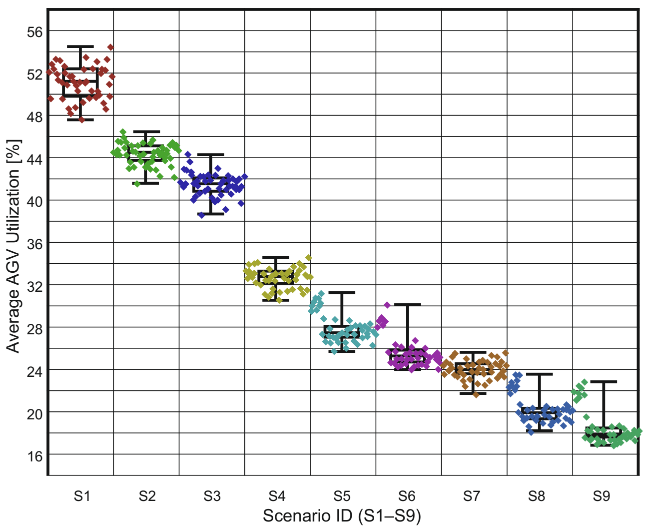


Fig. 6. Average AGV utilization across experimental scenarios (Variant I – random storage allocation)

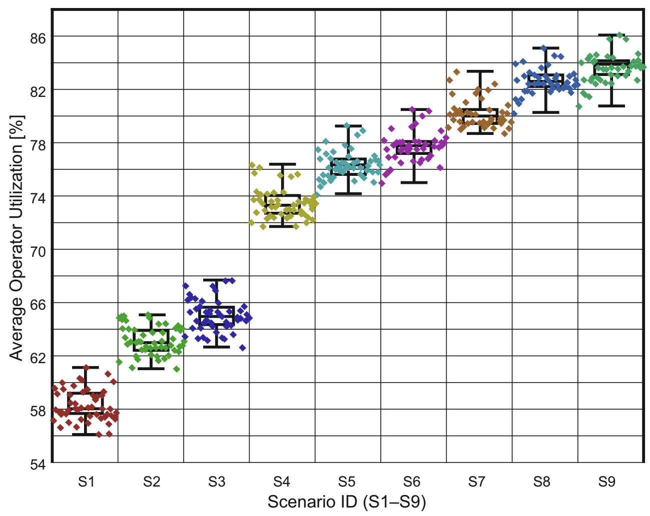


Fig. 8. Average operator utilization across experimental scenarios (Variant I – random storage allocation)

Figure 7 shows the utilization level of the combiners (average combiner utilization). In the random placement variant, the load on these objects is relatively even; however, a tendency for temporary overload is visible, especially in scenarios with a greater number of AGVs, which deliver component batches faster than operators can process them.

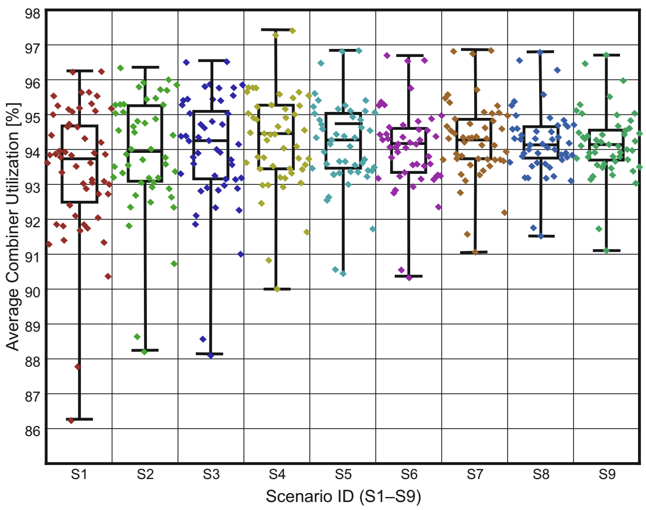


Fig. 7. Average combiner utilization across experimental scenarios (Variant I – random storage allocation)

Figure 8 presents the average utilization level of the operators (average operator utilization). The results clearly show that operators constitute the primary bottleneck of the system, their utilization level is significantly higher than that of the AGVs, and in some scenarios, it reaches a level close to full capacity. This indicates the necessity of balancing the ratio between the number of operators and the number of AGV vehicles to avoid delays in the picking and assembly processes.

The final element of the analysis is the system costs with a variable number of operators. Figure 9 presents a comparison of six scenarios in which the number of operators ranged from one to six.. The transport parameters were fixed (1 AGV, capacity = 1). The results show that as the number of operators increases, the total system costs grow linearly, while the benefits in terms of shortening operational time decrease. This means that an equilibrium point exists between the minimum staffing level required to ensure process continuity and excessive staffing that does not translate into a proportional increase in efficiency.

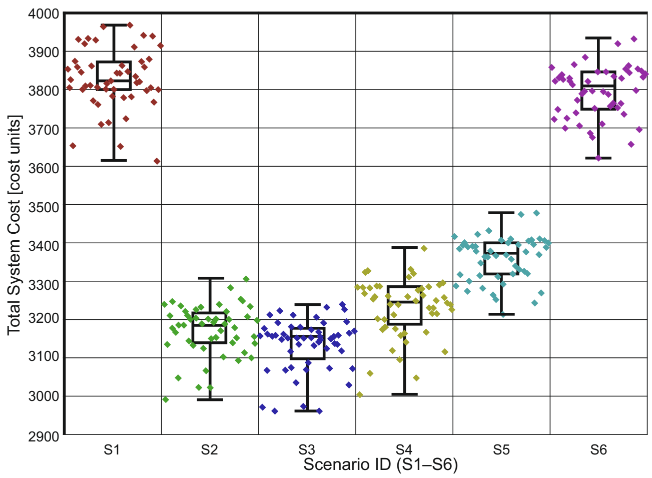


Fig. 9. Total system operating cost as a function of the number of operators (Variant I – fixed transport configuration)

In summary, the random placement variant fails to ensure balance between the utilization of technical and human resources, resulting in both reduced transport effectiveness and increased operating costs. Additionally, a significant scatter of results from individual simulations is noticeable, as confirmed by the box plots, which indicates low predictability and high sensitivity of the system to random location assignment. This type of variability further complicates resource planning and the stable functioning of the system. Therefore, even at this stage, it can be concluded that optimization of component routes and locations should bring significant benefits in terms of the stability and predictability of material flows.

4.2. Variant II – optimized placement

In the second scenario analyzed, a strategy of assigning components to fixed locations in the storage area was adopted. This placement resulted from the application of the OptQuest optimizer integrated into the FlexSim environment [12]. The optimization process considered two objective functions:

- Minimization of the total travel distance (Travel Distance).
- Minimization of total system costs (Cost), covering the costs of operator labor, assembly station operation, and AGV operation.

The following variables were adopted as decision variables:

- The permutation sequence defining the assignment of load units to fixed locations in the storage area (based on the global "Deliveries" table).
- The number of AGVs (from one to three).
- The capacity of a single AGV (from one to three load units).
- The number of operators servicing the assembly stations (from one to six).

In the optimization setup, 500 candidate solutions were generated, from which the ten best solutions were selected, forming the Pareto set. This approach allows for the identification of a Pareto frontier representing trade-offs between conflicting objectives, rather than a single optimal solution. Figure 10 presents the results of this optimization, where each point corresponds to one system configuration (a combination of the number of AGVs, their capacity, the number of operators, and the sequence permutation [1–15] assigning component types to storage locations).

The analysis of Fig. 10 indicates that the system is characterized by a clear trade-off between cost minimization and travel distance minimization. Solutions with the shortest transport routes usually involve a greater number of resources (AGVs and operators) and, consequently, higher costs. Conversely, variants with the lowest costs feature limited resource staffing, which increases the total distance and job completion time.

Figure 11 presents a comparative analysis of key performance indicators for the selected Pareto-optimal solutions. Part 11a presents the total AGV travel distance, Part 11b the corresponding costs, and Part 11c the total job completion time. Each scenario is designated by a symbol (AGV, Capacity, Operators), where the numbers in parentheses indicate the number of vehicles, their capacity, and the number of operators, respectively.

The comparison of the three indicators confirms that minimizing one criterion does not automatically lead to the optimization of the entire system. For example, scenarios S139 and S148 (2, 3, 5) achieved very favorable completion times, but at the cost of long AGV routes. Conversely, scenarios S462 and S503 (1, 3, 4) resulted in some of the shortest transport routes, yet their costs and times were higher than in other variants. Ultimately, the most favorable solutions represent a compromise among

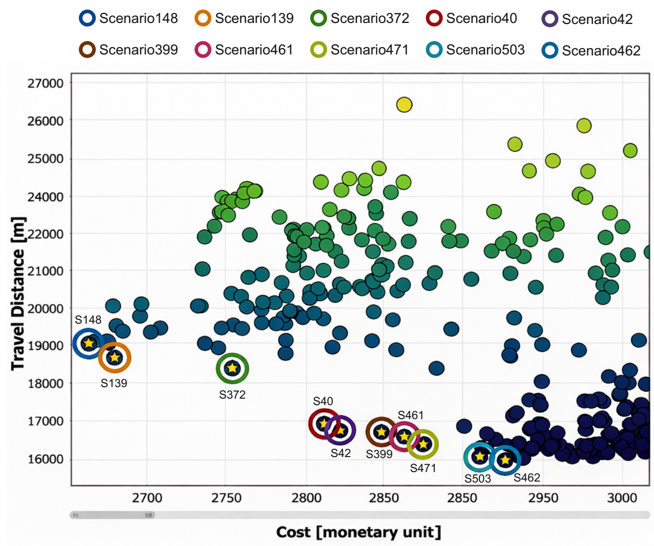


Fig. 10. Pareto set of optimized solutions illustrating the trade-off between total AGV travel distance and total system cost (Variant II)

these three criteria, confirming the necessity of a multi-criteria approach in the optimization process of intralogistics systems.

Further analysis of the results includes comparing the utilization level of the three main resource groups: AGV vehicles, combiners, and operators. Figure 12 summarizes the average utilization levels of the main resource groups across the optimized scenarios.

AGV utilization fluctuates between 28% and 41%. The highest values were recorded in scenario S372 (1, 2, 4), where the vehicle was intensively utilized with a relatively small number of resources (1 AGV with a capacity of 2 and 4 operators). Lower values (below 30%) were obtained in scenarios with greater resource staffing, which confirms the effect of distributing transport tasks among a larger number of units.

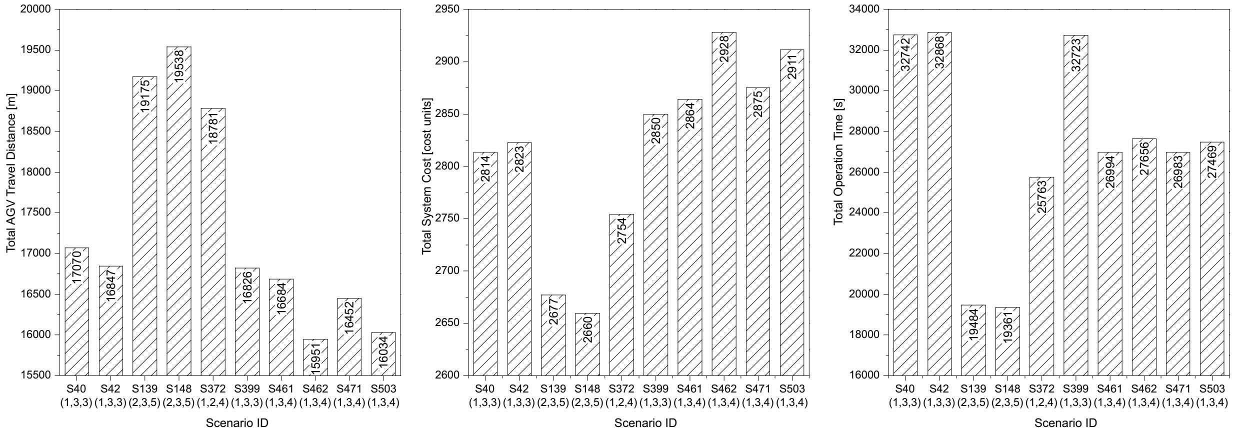
The utilization level of the combiners is significantly higher, ranging from 73% to nearly 97%. The most heavily loaded scenarios were S139 and S148 (2, 3, 5), in which two high-capacity AGVs and five operators were used.

This configuration caused the combiners to operate at the limit of their throughput, making them a key system constraint. Scenarios with a lower load (for example, S40 and S42) indicate greater reserves in this subsystem.

Operators achieved an average utilization level between 72% and 81%. Variants with a smaller number of operators (for example, S372 or S399) led to their high load (above 80%), while in scenarios with greater staffing (for example, S462 or S503 – four operators), the utilization level dropped to about 72–74%. These results clearly indicate that the number of operators is the key factor balancing the load between technical resources (AGVs) and workstations (combiners).

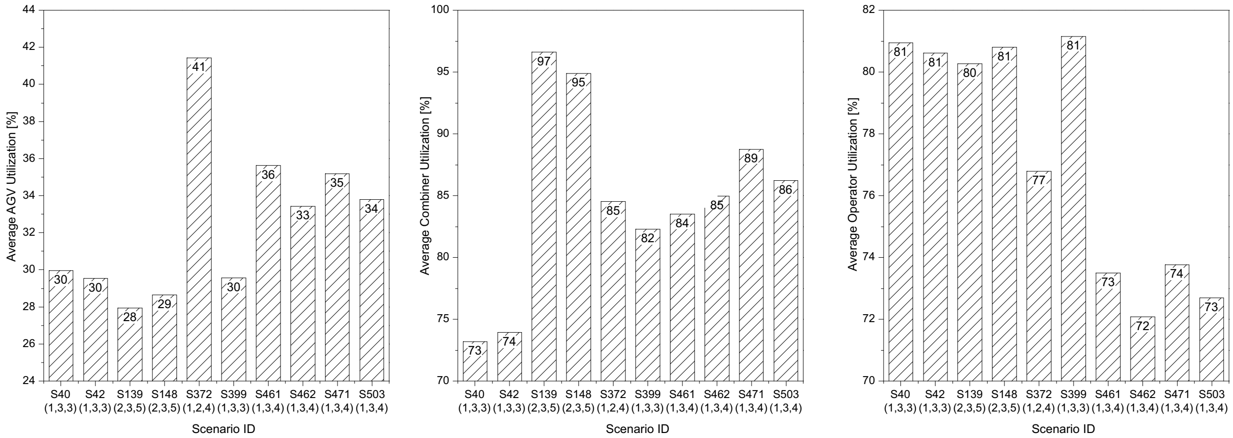
Figure 13 presents additional indicators related to the fluidity of the transport system:

- Wait count: The number of AGV vehicle blockages.
- Reroute count: The number of route recalculations enforced by traffic disruptions.
- Wait total [s]: The total duration of vehicle blockages.



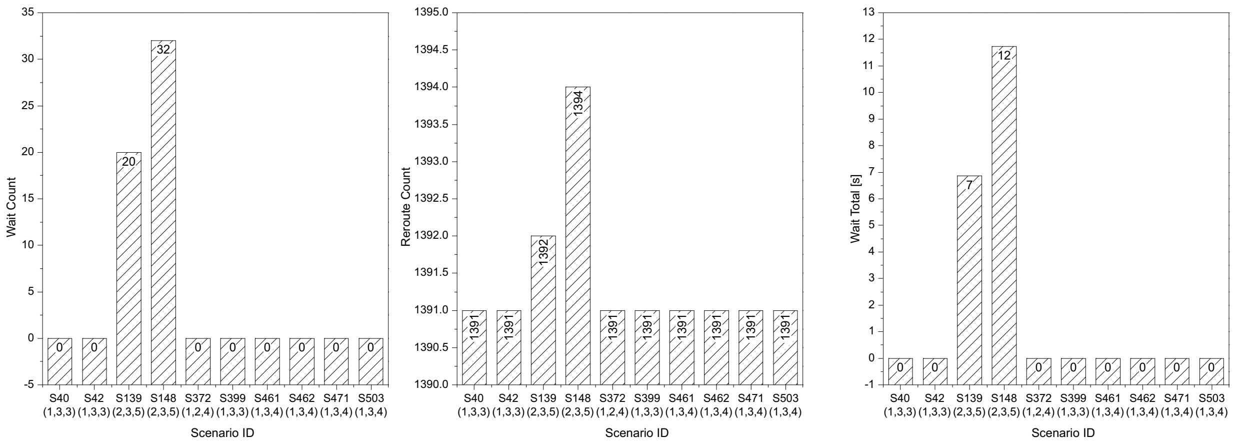
(a) (b) (c)

Fig. 11. Comparison of key performance indicators for selected Pareto-optimal solutions: (a) total travel distance, (b) total system cost, (c) total operation time (Variant II)



(a) (b) (c)

Fig. 12. Average utilization of AGVs, combiners, and operators across selected optimized scenarios (Variant II)



(a) (b) (c)

Fig. 13. Comparison of disturbance-related indicators in optimized scenarios: (a) wait count, (b) reroute count, (c) total waiting time

The results unequivocally indicate that no blockages occurred in scenarios with a single AGV vehicle (for example, S40, S42), and the number of route recalculations remained at a minimal level. This means that the risk of collisions and bottlenecks is negligible in a system with a single autonomous AGV vehicle.

To supplement the analysis of the aggregate optimization results (Figs. 11, 12), two selected scenarios were analyzed in detail: S372 (1 AGV, capacity 2, four operators) and S40 (1 AGV, capacity 3, three operators). The selection of these variants was dictated by their differing nature of resource load – in one case, the constraints are the technical devices (combiners), and in the other, the human resources (operators). In scenario S372 (Figs. 14a–b), the combiners achieved very high utilization levels, exceeding 90% in the case of some units (Combiner4 – 92.37%, Combiner5 – 91.44%). Simultaneously, a significant variation in operator load was visible – from 59.6% for Operator_4 to 89.1% for Operator_1. This indicates that despite the good availability of the transport system, the processing and picking capacity of the combiners becomes the bottleneck in this variant.

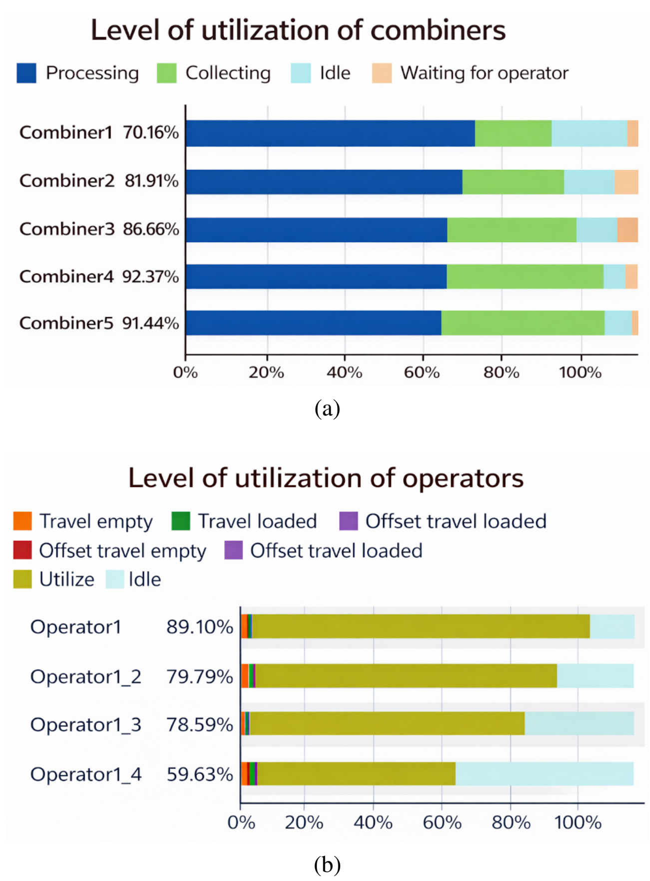


Fig. 14. Level of utilization in scenario S372 of: (a) combiners, (b) operators

In scenarios with a larger number of vehicles (for example, S139 and S148), a significant increase in the number of blockages was recorded – 20 and 32 instances, respectively, along with a noticeable duration of these blockages (7 s and 12 s). The number of route recalculations also increased in these same configurations (1392 and 1394), confirming that a growing number of AGVs increases the risk of overloading the transport network and necessitates dynamic obstacle avoidance.

In the remaining scenarios, the number of blockages and the waiting time remained zero, which suggests that these issues mainly occur in configurations that combine a high number of AGVs with high capacity and a significant number of operators, all of which intensify the material flow stream.

Conversely, in scenario S40 (Figs. 15a–b), the situation was different, with a more balanced utilization level of the operators, yet simultaneously higher (ranging from 68.7% to 91.7%). Although the load on the combiners was lower here (59–82%), the system relied more heavily on human labor. In the longer term, this configuration may lead to operator overload, increased turnover, or a decline in productivity due to fatigue.

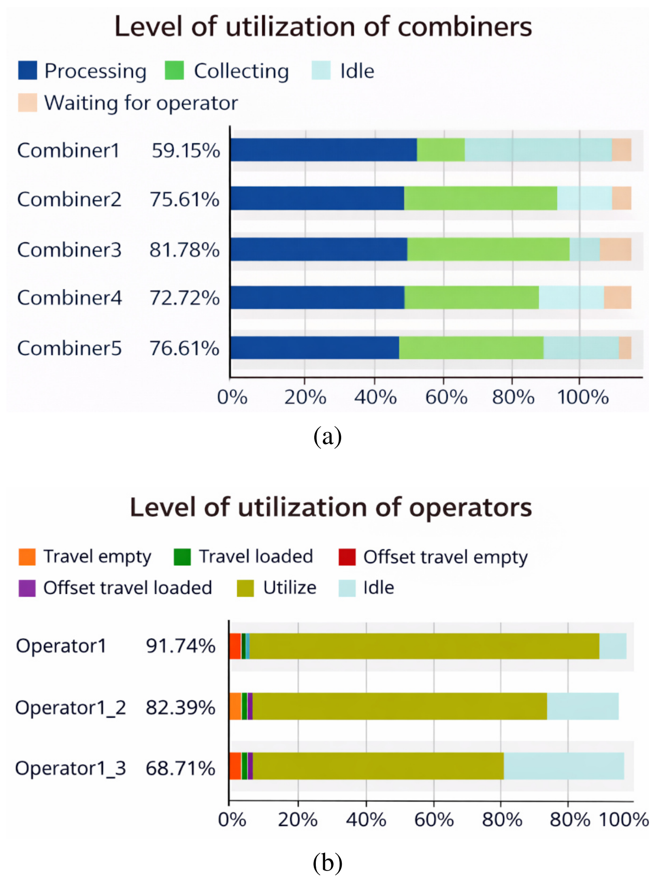


Fig. 15. Level of utilization in scenario S40 of: (a) combiners, (b) operators

The comparison of both variants reveals a clear trade-off: increasing the number of operators reduces pressure on human resources but leads to more intensive machine utilization and the risk of overloading their throughput capacity. Conversely, limiting the number of operators relieves the combiners but at the expense of greater employee involvement. In practical terms, this indicates the need to balance the level of automation and the share of manual labor, depending on organizational priorities (for example, minimizing labor costs versus reducing the risk of technical overload).

As illustrated in Table 3, scenario S372 is characterized by a higher load on the combiners (averaging 84.85%) and simultaneously significant, though not maximal, utilization of operators (76.78%). In contrast, a clearer pressure on human resources is evident in S40, in which operators work at an average level of 80.95%, while the combiners are less loaded (73.17%). AGV utilization is 41.43% in S372 and 29.95% in S40, which further confirms that in S372, machines are more intensively exploited (with better distribution of work among operators), while in S40, a greater burden of work rests on human resources.

Table 3
Comparison of resource utilization for scenarios S372 and S40

Scenario	AGV utilization [%]	Avg. combiner utilization [%]	Avg. operator utilization [%]
S372 (1 AGV, cap. 2, 4 operators)	41.43	84.85	76.78
S40 (1 AGV, cap. 3, 3 operators)	29.95	73.17	80.95

A practical conclusion is the necessity of balancing the number of operators and the degree of automation. Increasing the operator staffing reduces pressure on personnel but may shift the bottleneck to the equipment (combiners). Conversely, reducing the number of operators places a greater burden on personnel, even though some reserve remains from the perspective of AGV operation.

The results provide a foundation for recommendations regarding optimal staffing and further testing (for example, investigating the impact of redistributing tasks among operators or increasing the number of combiners). This directly addresses the need for an integrated approach that considers both financial implications and human resource utilization alongside technical efficiency.

It should be noted that the analyzed scenarios represent selected configurations within a defined parameter space and do not cover all possible system configurations. The purpose of the analysis is, therefore, comparative rather than exhaustive.

The obtained results are consistent with findings reported in the literature on intralogistics and production system optimization. Previous studies have emphasized that the efficiency of internal transport systems strongly depends on the appropriate configuration of resources and layout decisions [5, 6]. In particular, the importance of integrating transport system parameters with storage allocation strategies has been highlighted in works related to warehouse optimization and AGV-based systems [20, 26].

The observed trade-off between minimizing transport distance and minimizing operational costs is also in line with multi-criteria optimization approaches discussed in the literature [16, 36], where improving one performance indicator often leads to deterioration in another. This confirms the necessity of applying Pareto-based methods in complex intralogistics systems.

Furthermore, the results underline the critical role of human resources in hybrid systems, which has been pointed out in studies on human–machine integration in assembly environments [7]. The high utilization levels of operators observed in several scenarios confirm that human-related constraints remain a key factor limiting system performance, even in highly automated environments.

From a broader perspective, the results confirm that effective optimization of intralogistics systems requires a holistic approach that considers not only technical parameters but also organizational and economic aspects. This observation is consistent with the principles of modern production system design, including Industry 4.0 and Industry 5.0 paradigms.

4.3. Comparative summary and limitations of the study

The comparison of the two analyzed variants clearly indicates the superiority of the strategy based on the assignment of fixed, optimized storage locations over the random variant. Variant II provided clearly shorter travel routes for the AGV vehicle, which also translated into a reduction in the total operational time of the system. The largest differences were visible in configurations with higher vehicle capacity, where savings in route length and operational time exceeded 10%. The optimized variant was also characterized by greater system stability, as reflected by the smaller dispersion of results, and the number of disturbances related to blockages and route collisions was significantly lower than in the case of random component placement.

Differences between the analyzed variants were also visible in the level of resource utilization. In the random setup, large fluctuations in AGV load and inconsistent utilization of combiners and operators were observed, which is confirmed by both the results regarding the total number of blockages and vehicle waiting time, as well as greater variability in the load distribution of resources. The optimized variant allowed for a more even distribution of tasks among resources, reducing the risk of bottlenecks and improving the fluidity of material flow. More favorable results were also observed with respect to cost-related indicators, expressed using the adopted cost rates for AGV operation and operator labor.

It should be emphasized, however, that the results obtained are model-based and are associated with certain limitations. The model was based on exemplary data, which allowed for a controlled comparison of the variants but did not reflect the full complexity of real production processes, such as demand variability, supply disruptions, or planning errors. Furthermore, the assumptions regarding operator activities were simplified; their role was limited to servicing combiners, without considering additional activities performed in practice.

Limitations also concerned the adopted assumptions for the transport system. The AGVs moved along a fixed network of routes, which allowed for precise analysis of their routes but did not account for potential strategies for dynamic traffic management. The cost analysis used averaged rates for AGV operation and operator labor, which may differ depending on the specificity of the enterprise and market conditions. Finally, the results obtained refer to a model of a specific size and configuration, and their direct transfer to other systems would require additional calibration.

Despite these limitations, the conducted research confirms that optimization of component placement in the assembly hall, combined with the appropriate selection of the number and capacity of AGVs and operator staffing, significantly improves the logistical effectiveness of the system. These results also emphasize the importance of integrating autonomous transport with human labor, indicating that only coherent management of both types of resources enables the achievement of measurable benefits in terms of time, costs, and operational stability.

5. CONCLUSIONS

This study evaluated two alternative component placement strategies in a hybrid assembly intralogistics system integrating AGVs and human operators. The simulation experiments conducted in the FlexSim environment made it possible to compare the performance of a random storage allocation strategy and an optimized storage assignment approach using selected operational and cost-related indicators.

The results indicate that the optimized variant provides more favorable system performance in terms of AGV travel distance, operational time, system stability, and resource utilization. In particular, the assignment of fixed, optimized storage locations contributed to shorter transport routes, lower variability of results, and a more balanced distribution of workload between AGVs, combiners, and operators.

The study also confirmed the existence of a trade-off between transport efficiency and total operating cost. Configurations with better transport performance often require a higher level of resource engagement, especially in terms of AGV capacity and operator staffing. This confirms that the design of intralogistics systems should not be based solely on technical performance indicators but should also include organizational and economic considerations.

An important conclusion from the study is that, despite the use of autonomous transport, human resources remain a critical factor in the performance of hybrid systems. In several analyzed scenarios, operators reached high utilization levels, indicating that labor availability and task allocation significantly influence the smoothness of material flow and the overall efficiency of the system.

At the same time, the study has several limitations. The model was developed using a simplified production layout and exemplary input data, which allowed for controlled comparative analysis but does not reflect the full complexity of real industrial systems. In addition, the AGV subsystem was modeled using a fixed transport network and predefined control logic. Therefore, the model does not include more advanced real-time fleet management mechanisms, such as AI-based dynamic task allocation, adaptive rerouting, or predictive traffic control. These aspects remain beyond the scope of the present study and constitute a promising direction for future research.

Future work may therefore include the integration of more realistic operational data, dynamic dispatching strategies, and expanded decision variables related to scheduling and traffic control. Nevertheless, the presented approach confirms that simulation combined with optimization constitutes an effective decision-support tool for the design and improvement of hybrid intralogistics systems in assembly environments.

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