Agent-Based Simulation Study for Improving Logistic Warehouse Performance

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Abstract

Logistic warehouses are critical nodes in a supply chain and improving their performance is a crucial issue when trying to avoid unproductive bottlenecks. Warehouse optimization involves several problems, some of which must be considered at the design stage and others during real-time operations. In this study, we performed an agent-based simulation to analyze the behavior of automatic logistic warehouses under the influence of specific factors, thereby obtaining indicators to supporting decision making during warehouse performance improvement. This study focused mainly on automatic warehouses where goods are moved by automatic guided vehicles.
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Introduction

Logistic Warehouses are strategic locations for receiving, storing, and redistributing products. Improving performance and decreasing costs are issues that must be addressed to improve logistic processes. Unfortunately, the great number of variables that affect the performance and costs of warehouses make it difficult to determine effective choices during warehouse optimization. Tools and methods are essential for supporting decision making and management processes. In particular, the use of simulations has been studied by several researchers (Bonini, 1963; Macro and Salmi, 2002; Lee et al., 2003; Chen et al., 2013) as an alternative approach to conventional techniques. Simulations can be used in different contexts for evaluating the behavior of complex systems, where conducting simulations allows alternative decisions to be examined. The effects of these alternatives can be tested without conducting experiments in a real environment, which is often prohibitive in terms of cost or completely unfeasible. In many practical fields, simulation is the most affordable way of understanding how the numerous variables interact and constrain the performance of systems.

The present study considered automatic logistic warehouses where inbound and outbound activities are performed by automatic transportation systems using optical guidance called automatic guided vehicles (AGVs), and where incoming goods are forwarded directly to new destinations (there is no storage). By analyzing this real case study, we show that a common physical configuration (see Figure 1) for this type of warehouse comprises: 1) a set of *gates* where lorries are parked to unload their cargo; 2) a set of *recharging areas* where AGVs recharge their batteries; 3) a *sorting area* where goods are processed and forwarded to a new destination; 4) a *buffer area* where unidentified goods are placed temporarily; 5) a set of AGVs; 6) a set of *waypoints*, which are landmarks for AGV navigation; 7) a set of optical *paths* for AGV navigation, where each path is represented by a set of *segments* (i.e., parts of the path included between two waypoints).

Improving the performance of this type of warehouse basically involves increasing the

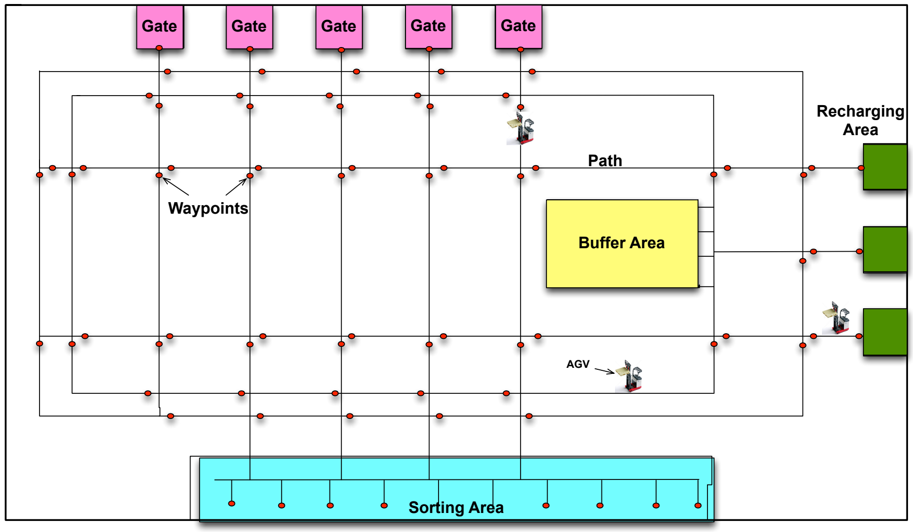


Figure 1: Typical configuration of a warehouse.

amount of goods forwarded toward a new destination. This mainly depends on the efficiency of an AGV, which can be influenced by several factors, such as the warehouse's physical configuration and management strategies.

The main objective of this study was to investigate the behavior of automatic logistic warehouses under the influence of specific factors (i.e., layout configurations, AGV fleet size, and management strategies) in order to obtain indicators that might support decision making during warehouse performance improvement. To achieve this aim, we developed an agent-based simulation model to represent several factors that coexist simultaneously and influence warehouse performance. Hence, we performed a simulation study using this model, where we considered a real case study provided by an industrial project. In some cases, simulation studies can validate expected qualitative results as well as providing quantitative measures related to alternative choices. In other cases, unexpected results can emerge.

The remainder of this paper is organized as follows. Section II provides an overview of related research. Section III provides an overview of agents and simulations. In Sections IV and V, we describe the agent-based simulation model and the experimental setup, respectively. We analyze the numerical results in Section VI. Finally, we give our conclusions in Section VII.

Related Work

Many approaches have been developed in recent years in order to address different logistic warehouse problems with the aim of increasing performance (Gu et al., 2007, 2010). The aim of the present study was to analyze the behavior of automatic logistic warehouses under the influence of specific factors such as the layout configuration, AGV fleet size, and management strategies.
Recently, many studies have considered the layout configuration because it has a significant impact on manufacturing costs, warehouse processes, and productivity. A layout comprises a spatial arrangement of the physical resources used for creating a product or providing a service (Tompkins et al., 2010; Taylor and Russell, 2000). An appropriate arrangement of resources (i.e., facility layout design (Taylor and Russell, 2000)) contributes to the overall efficiency of business organizations (Drira et al., 2007). Many studies have investigated the facility layout problem because numerous issues

need to be considered in layout design (Niroomand, 2013; Drira et al., 2007). The layout problem is highly dependent on the specific features of the production system under study, such as the production variety and volume, material handling system selected, number of floors where the machines work, and the pick-up/drop-off locations.

For the layout problem that depends on the product variety and production volume, the following four main types of layouts have been studied previously (Drira et al., 2007; Hasan et al., 2012; Pisaruk, 2012).

- *The product layout* (Jarvis and McDowell, 1991; Chen et al., 2011) is used for systems with high production volumes and a low variety of products. The facilities are organized according to the sequence of the operations that need to be accomplished. Common product layouts are used in production lines such as those for producing shoes and cars. In this type of layout, the products generally circulate within the production facilities (e.g., machines and workers).

- *The fixed product layout* is similar to that described above but the product does not move. The different resources are moved in order to perform operations on the product.

- *The process layout* (Khalili-Damghani et al., 2014) is a configuration where facilities with similar functions are grouped together (resources of the same type). Hospitals are a typical example where areas are dedicated to particular types of medical care.

- *The cellular layout* (Ariafar and Ismail, 2009; Morad, 2015) groups dissimilar machines into cells to work on products with similar shapes and processing requirements. This is similar to the process layout because the cells that are designed to perform a specific set of processes, but also similar to the product layout because the cells are dedicated to a limited range of products. The problem basically involves finding the best arrangement of machines in each cell.

For layout problems that also depend on the material-handling device, two dependent design problems must be considered: finding the facility layout and selecting the handling equipment (Drira et al., 2007). Indeed, the type of material-handling device influences the layout pattern used and the layout also affects the selection of the handling device (Devise and Pierreval, 2000).

Tompkins *et al.* (Tompkins et al., 2010) suggested that the influence of material-handling systems cannot be neglected because their costs represents 20–50% of the total operating costs and a good arrangement of facilities may reduce the costs by 10–30%.

Material-handling systems are diverse, including many possible technological solutions, which range from workers to conveyors and AGVs, and each affects the problem in a different way. Devise and Pierreval (Devise and Pierreval, 2000) provided performance indicators for helping a designer to find good layouts and material-handling system solutions.

Many studies have evaluated the performance of the major types of layout arrangements based on the type of material-handling systems (Drira et al., 2007). The three major types of layout arrangements are single-row, multi-row, and loop layouts.

The *single-row layout* is used mainly when the items follow the same machine sequence. In the single-row layout (Solimanpur et al., 2005; Anjos and Vannelli, 2008; Keller and Buscher, 2015), facilities must be placed next to each other along a line in order to minimize transportation costs among the facilities.

By contrast, the *multi-row layout* (Na et al., 2010) is used when it is permissible to move items from any machine to any other machine. Thus, the flow of items need not be unidirectional.

Finally, in the *loop layout* (Cheng and Gen, 1998; Tansel and Bilen, 1998; Kumar et al., 2008), the machines are arranged in a loop network and the materials are transported in a single direction. An important step when designing a unidirectional network is determining the or-

der of the machines around the loop.
Many researchers have proposed exact and heuristic approaches to solve this problem(Keller and Buscher, 2015), including mathematical programming (Heragu and Kusiak, 1991; Amaral, 2006), dynamic programming (Picard and Queyranne, 1981; Kouvelis and Chiang, 1996), branch and cut (Amaral and Letchford, 2013; Anjos and Vannelli, 2008), simulated annealing (Kouvelis and Chiang, 1996; Heragu and Alfa, 1992), ant colony optimization (Solimanpur et al., 2005), tabu search (Samarghandi and Eshghi, 2010; Kothari and Ghosh, 2013), genetic algorithms (Datta et al., 2011; El-Baz, 2004; Vitayasak and Pongcharoen, 2015), Monte Carlo simulation (Chan and Malmborg, 2010), and other heuristics (Kumar et al., 1995; Djellab and Gourgand, 2001).

In the present study, we aimed to measure the performance of predefined warehouse layouts under the influence of AGV systems, as well as comparing different management strategies. We addressed this question using a simulation-based approach. In particular, we employed the "layout then simulate" paradigm (Aleisa and Lin, 2005).

Layout studies based on this paradigm start with predefined layouts, which can be generated using facility layout routines. Hence, improving the operational characteristics is based on the results of a simulation study. Applications based on this approach typically assume that the overall production strategies and manufacturing technologies are predetermined, where the objectives involve comparing, testing, adjusting, and validating different layout configurations (Aleisa and Lin, 2005).

In particular, we focused on specific aspects of the use of AGVs for handling goods. AGVs are autonomous vehicles with optical guidance systems, which are used widely to transport materials in flexible manufacturing systems and to perform other tasks that involve automation in industrial environments. The use of AGVs means that further issues need to be considered, such as the minimum number of AGVs required to complete warehouse processes (the AGV fleet size), the unloading policies, and the routing strategies employed according to the warehouse layout.

The number of vehicles and their efficiency greatly influence the performance of a warehouse. A high number of vehicles will incur greater costs and may cause traffic congestion. By contrast, underestimating the vehicle fleet size means that a warehouse may work below its full capacity. Several approaches have been proposed to address this issue using analytical methods. *Ji* and *Xia* (Ji and Xia, 2010) presented an approximate analytical method for estimating the interval of the minimum vehicle number in order to guarantee the stability of the system. In particular, their model considers the number of orders waiting at depots as a parameter for evaluating the stability of the system. The system is in a stable state if the number of waiting orders remains at a stable level. *Hall et al.* (Hall et al., 2001) proposed an approach for minimizing the AGV fleet size by traveling in a loop layout while minimizing the cycle time. *Robert and Egbelu* (Arifin and Egbelu, 2000) used a regression technique to estimate the vehicle number required by a depot. *Kasilingam and Gobal* (Kasilingam and Gobal, 1996) presented a simulation-based cost model for determining the number of AGVs needed to meet the material-handling requirements in a manufacturing system. The number of vehicles is estimated based on the sum of the idle-time costs of vehicles and machines, and the cost of the waiting time for parts. *Swaminathan et al.* (Sai-nan, 2008) proposed a genetic algorithm for solving the AGV fleet optimization problem. The model was simplified by assuming that the traveling speed of every vehicle is invariable by neglecting the stopping and start-up time of AGVs, where the vehicle stops at the nearest storage when the current task is finished and the sorting tables are sufficiently large. *Vis et al.* (Vis et al., 2001) developed a minimum flow algorithm for determining the minimum number of AGVs to transport all the containers in a semi-automated container terminal within a time window. The approach proposed by *Yifei et al.* (Yifei et al., 2010) relies on two procedures (estimate and simulate) for determining the AGV fleet size, where a mathematical method is used to estimate the AGV fleet size and the estimated value is used in the simulation model of the system. *Kahraman et al.* (Kahraman et al., 2008) built an analytical model that uses a Markov chain approximation approach to evaluate the performance of AGVs and to optimize the capacity in a closed-loop path.

Other studies have proposed management strategies with the aim of identifying efficient approaches. AGV routing strategies are often treated as vehicle routing problems, which basically involve determining m vehicle routes and minimizing the total distance of all routes. *Krishnamurthy et al.*(Krishnamurthy et al., 1993) developed a column generation method for the static routing problem where an AGV has to move in a bidirectional conflict-free network. *Maza* and *Castagna* (Qiu and Hsu, 2000) proposed a robust predictive method for routing without conflicts. *Möhring et al.* (Möhring et al., 2005) proposed an algorithm for the AGV routing problem without conflicts at the time of route computation. In (Yoo et al., 2005), an adaptable deadlock avoidance algorithm was presented for an AGV system, where the dynamic resource allocation policy decides how each AGV will request a resource and how it affects the resource utilization and throughput.

Many studies in this research field have addressed the size of the AGV fleet, routing strategies, and scheduling policies separately.

In this study, we considered the joint effect of various factors on warehouse performance by developing an agent-based model of a logistic warehouse, which globally addresses all the aforementioned issues. This model allowed us to evaluate the overall behavior of a warehouse and the effects of each factor on others. The results of the simulation study performed using this model determined the correlations (if any) among different factors.

In the following section, we provide a brief overview of agent-based modeling and simulation to explain the reasons why we selected this method.

Overview of Agent-based Model Simulations

Agents are autonomous entities that can work independently and/or cooperate with other agents in order to achieve some goals. They are usually placed in an environment that they can perceive and interact with (Wooldridge, 2001). A multi-agent model is a representation of an original system where the entities involved are agents situated in a virtual environment, which reproduces the original. In a multi-agent simulation, real-world system operations can be tested over time experimentally by executing a multi-agent model, where the agents and environment are essential parts of the multi-agent simulation model (Klügl et al., 2005).

Agent-based modeling approaches (Macal and North, 2010) also allow us to model social relationships and the organizational forms of a real system. Several studies (Wooldridge, 2001; Georgé et al., 2003; Macal and North, 2010) have shown that agent-based simulations are effective tools for simulating complex systems containing large numbers of active entities (people, business units, and vehicles), which have specific timings, event orderings, or other types of individual behavior associated with them. It has been claimed (Borshchev and Filippov, 2004) that agent-based models (ABMs) are more general and powerful compared with other modeling approaches because they allow more complex structures and dynamics to be described. Their main advantages compared with other classical approaches are as follows.

- ABMs are essentially decentralized. In contrast to system dynamics or discrete event models, there is no place to define the global system behavior in an ABM. Thus, it is possible to build ABM models without knowledge of the global interdependencies. The modeler may know very little about how the elements of the model affect each other at the aggregate level, or the global behavior of the system. Thus, a modeler can develop ABMs by starting from the individual behaviors of the entities involved in the system. The global behavior of the system emerges from the interactions among individual entities, where each follows its own behavior rules and they inhabit the same environment (Borshchev and Filippov, 2004).

- In ABMs, there is an intuitive ontological correspondence between agents and the real-world actors. Agents can be heterogeneous in the same model. Thus, agent features and behaviors can be different. Agents can be endowed with different resources and capacities. There is a natural translation between the virtual world where the agents act and the real part of the world where the simulated system is located. ABMs can incorporate discrete-event simulation mechanisms (Borshchev and Filippov, 2004).

- ABMs have great flexibility and efficiency when modeling different types of systems. ABMs are suitable for modeling systems where entities interact frequently with each other. Discrete-event simulations have various world-views (e.g., event-scheduling or process interaction), which vary greatly in terms of their modeling flexibility and analytical power. However, in general, discrete-event simulations focus on simulating events and their relationships in the underlying discrete-event dynamic system. The events can be general in discrete-event simulations. The actions taken by each agent at each time step in an ABM can be considered as events, and thus they can modeled using a discrete-event simulation approach. However, discrete-event simulations can exponentially increase the number of events, thereby making the model inefficient and difficult to analyze (Chan et al., 2010). Discrete-event simulations are not appropriate when the state variables interact with each other and they change continually, and when entities and their internal mechanisms are more important elements of the simulation than events (Borshchev and Filippov, 2004).

- Moreover, ABMs are well suited to visualization. The actions and interactions of agents in an ABM usually have direct physical interpretations, which are suitable for animation. Animation is a way of visualizing the dynamics and interactions of agents, as well as a powerful method for verifying, validating, and explaining the model.

- ABMs are usually easier to maintain, where model refinement generally results in very local (not global) changes.

These features allow us to represent certain aspects that are very difficult to represent using other types of modeling (Siebers et al., 2010). In our study, the use of an ABMS approach provides a natural way of modeling the heterogeneous entities (AGV, sorter, etc. . .) involved in the warehouse processes, warehouse organizational schemes, and the physical environment where these entities act. As shown in the next section, the use of an ABM facilitates a strong conceptual similarity between the model and the real system. The behaviors of the real-world entities (AGV, sorter, etc. . .) are represented directly by the agents in the model. The behavior of the overall warehouse system results from the interactions among agents as a macro-level phenomenon. This approach makes the model more intuitive and easier to deal with than other types of modeling. In addition, our warehouse system is characterized by active entities (AGVs), which the ABM can model in an appropriate manner.

In the following section, we present the agent-based simulation model of a logistic warehouse.

Simulation Model of a Logistic Warehouse

The warehouse simulation model was designed according to the methodological approaches proposed by (Ribino et al., 2014, 2015). These approaches provide some guidelines for addressing different concerns about the elements that need to be modeled in agent-based simulations. The proposed warehouse simulation model combines three views of warehouse modeling from different perspectives: *(i)* the *environment model*, *(ii) organizational model*, and *(iii) behavioral model*. The overall behavioral model of the system comprises a set of single behavioral models for each active entity in the organizational model.

The *environment model* represents the physical and functional features of a warehouse, which comprise four main elements: (i) *actors* that act as entities populating the warehouse; (ii) *artifacts* as passive objects that determine the physical aspects of the warehouse; (iii) *actions* that actors can perform in the warehouse in order to complete some processes; and (iv) *percepts*, which are domain-specific concepts that an actor is able to manage.

The *organizational model* specifies the organizational schema adopted by the entities involved in the warehouse processes. It is based on three elements: (i) *roles* comprising a set of capacities and a set of obligations and responsibilities. A capacity represents the competencies required to achieve some functionality in a specific context independent of the way it is completed (Ribino et al., 2015); (ii) a *group* is defined as a collection of roles that participate in interactions with other roles in a predefined context; and (iii) *communications* are links between the roles involved in some exchange of information.

The *behavioral model* describes the dynamic behavior of each role in the organizational model, which is based on two elements: (i) *plans* comprising a set of actions that define the behavior of an entity in the warehouse; and (ii) *events* are specifications of an occurrence that might potentially trigger effects on the system.

This conception of the overall model facilitates a simple implementation using Jason and Moise. Jason (Bordini et al., 2007) is a Java-based interpreter for an extended version of AgentSpeak (Rao, 1996), which is a Prolog-like logic programming language based on the BDI (*Beliefs*, *Desires*, *Intentions*) paradigm (Rao and Georgeff, 1995). Jason provides relevant utilities for the implementation of multi-agent systems and for defining the environment. In addition, Moise (Hubner et al., 2007) natively manages concepts such as groups and roles, which have direct mappings onto real organizational forms.

In this study, we developed a model based on the requirements for a real logistics warehouse where goods transportation is performed by AGVs.

Scenario - The scenarios analyzed to extract the elements that must be instantiated in the model are representative of a large number of real logistic warehouses that employ forklifts for pallet handling. In these scenarios, several articulated lorries can arrive in a logistic district and each articulated lorry transports one 40-feet standard *International Organization for Standardization* (ISO) type container. When a lorry reaches the warehouse, it docks into a bay to unload its cargo. **On a normal working day, three gates are typically employed**. A container generally contains several types of goods in boxes, which are grouped on pallets (i.e., 800 $\times$ 1200 mm standard ISO pallets). Each pallet must be unloaded from the container and carried into a sorting area. In this area, each pallet is opened and its contents (i.e., packages of goods) are placed on the sorter. These operations take approximately 5 minutes for each pallet. The sorter clusters the packages according to their final destination. Finally, smaller vehicles (i.e., eco-friendly trucks) deliver these packages to their destinations. The pallets are moved by AGVs.

Two aspects are considered by the management strategies: the allocation of paths to AGVs and the unloading policy for the incoming goods. Decentralized approaches give AGVs more autonomy and flexibility (Weyns et al., 2005), but centralized approaches are still used at present due to safety issues. In this case, vehicles are controlled by a central component, which plans routes for AGVs according to the incoming transports. Thus, an

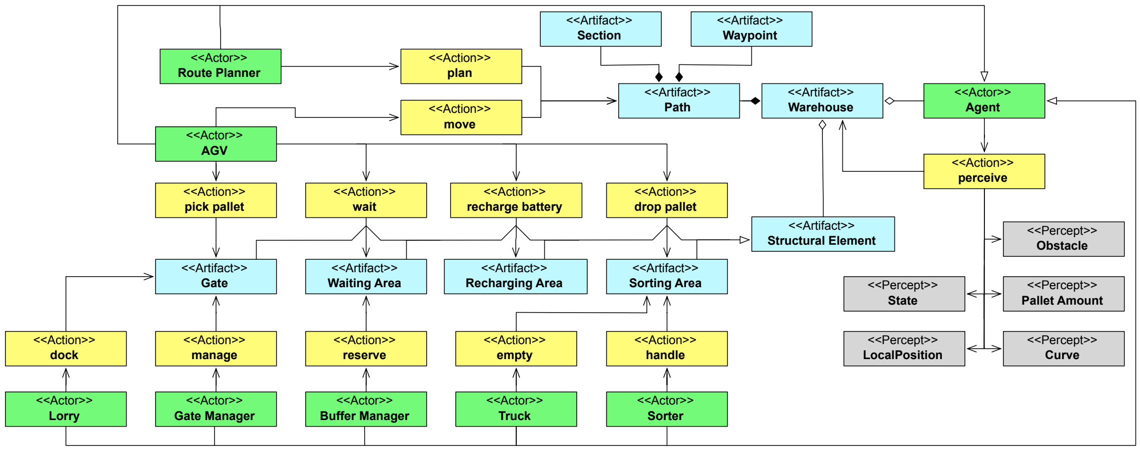


Figure 2: Environment model.

AGV is authorized to move only on an assigned path. In this study, we analyzed various path reservation strategies to allow the concurrent completion of paths by several AGVs. In these strategies, a path from a source to a destination is not assigned completely to a single AGV, but only to several segments at a time. These approaches have costs in terms of time. Indeed, when an AGV reaches the reserved portion of the path, it has to stop, find a new free path, reserve it, and then restart, which incurs a delay. Reserving very few path segments each time produces many requests, which may significantly delay the unloading operations. By contrast, reserving many path segments decreases the availability of free paths for the remaining AGVs, which must wait for their release. Thus, different approaches to path reservation can influence the performance of the warehouse.

We considered two different strategies for the unloading policy. The first policy is a nearest neighbor policy (NNP), where an AGV goes toward the nearest gate in order to unload a box of goods and then moves to the nearest free sorter to deposit the goods. The second policy is based on a priority policy (PP), where AGVs unload from gates with higher priority. When two or more gates have the same priority, the AGV moves toward the closest.

Environment Model - The environment model (see Figure 2) related to our case study depicts real warehouses, which are commonly situated inside logistic districts. The model comprises two categories of elements: *structural elements* and *paths*. A warehouse environment must contain at least one *path* that allows an AGV to reach each destination *waypoint*. Moreover, a *path* always comprises at least one *segment* and two *waypoints*. A *waypoint* is a reference point used for AGV navigation. *Structural elements* are artifacts that define the physical layout of a simulated warehouse (i.e., its architecture). The structural elements comprise a: set of *gates*, set of *recharging areas*, *sorting area*, and a set of *waiting/buffering areas*.

For the percepts, an agent knows the following: (i) *Obstacles* representing any type of object that differs from the artifacts. They can also be other agents. This knowledge allows agents to avoid collisions; (ii) *Pallet amount* defines how many pallets are in the warehouse, which allows the agents to plan and coordinate their activities; (iii) *Curve* is part of a path that differs from a straight line, where an AGV moves in a different manner; (iv) *State* is a particular condition assumed by an artifact (i.e., a gate can be busy or free); and (v) *Local position* refers to the position of a particular object. Agents can also perceive all the *artifacts*.

Finally, the *actions* that agents can perform on the elements of the warehouse are closely related to the artifacts. For instance, in order to occupy a place in a waiting area, the buffer manager must reserve it (i.e., register as busy), which also applies to a recharging area where an AGV recharges.

The environment model was implemented using the environment classes provided by the Jason tool, which are based on the classic model-view-controller architecture. The model component specifies all the features defined in the environment model (Figure 2). The view component defines the graphical aspects of the environment models that are suitable for visualization and animation. Finally, the controller interacts with agents as well as making changes to the model and the view according to the agent's actions.

Organizational model - The organizational schema (Figure 3) employed by the entities involved in the warehouse processes is represented as an organizational diagram (Cossentino et al., 2012b).

Layers and partitions are used to organize the architectureŠs topology into logically related subsystems. In particular, the proposed organizational schema (Figure 3) comprises two partitions *warehouse management society* and *road transport society*, which identify logically related components that provide services at the same level of abstraction. In order to comply with the ABM paradigm, we designated the layers and partitions as groups and their components as roles. Agents may play one or more roles according to their capacities.

In particular, the *road transport society* is a group that provides services for goods transportation from/toward a logistic district. The *warehouse management society* governs the activities inside a warehouse and it comprises two layers: the *management layer* dealing with the management of warehouse operations and the *operational layer* providing warehousing services.

The management layer comprises three roles: *gate manager*, *buffer manager* and *route planner*. The operational layer is formed of *sorter* and

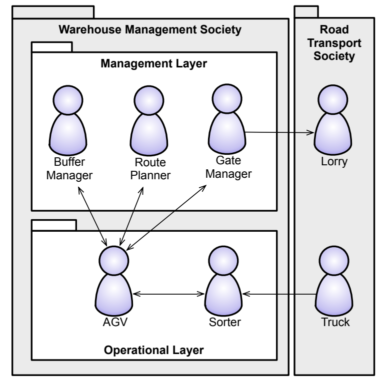


Figure 3: Warehouse organizational model.

AGV roles. The *road transport society* comprises two roles: *lorry* and *truck*. The following list explains each role.

- The *gate manager* manages the allocation of gates when *lorries* arrive and it assigns the missions.
- The *buffer manager* governs the waiting areas, where it can reserve parking places for agents that require them.
- The *route planner* allocates the paths for AGVs. It is also responsible for releasing the allocated resources.
- The *sorter* manages the work inside the sorting area. It can communicate the available places where it is possible to deliver a pallet. Moreover, the sorter interacts with trucks to forward the packages toward their new final destinations.
- An agent that plays the *AGV* role is responsible for unloading the goods that come into the warehouse and moving them to the sorting area.
- Finally, the *lorry* and the *truck* roles are responsible for transporting goods to and from a logistic district, respectively.

In our system, there is a one-to-one mapping between roles and agents.

A multi-agent structural description diagram (Cossentino et al., 2012a) is shown in Figure

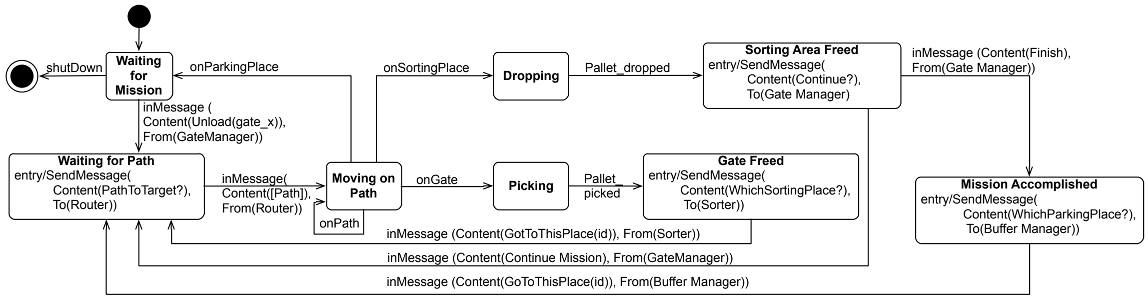


Figure 4: Behavioral model of the Agv's role.

5, which illustrates each agent. In this type of diagram, the body of an agent usually comprises four fields, which denote its initial beliefs (a priori knowledge about the world), initial goals (goals that the agents will attempt to achieve from the beginning), rules (beliefs derived from a logical consequence of other beliefs), and plans (the agent's knowledge). For example, the AGV role comprises an initial belief that introduces a random time during the execution of plans as well as a rule for distinguishing between a straight path and a curve when an AGV moves from a source to a destination. Initial beliefs, initial goals, and rules are not mandatory.

Figure 5 also shows the interactions (via communication relationships) among the agent's roles in the model. In our study, we assumed that communication comprised several messages ordered by an interaction protocol (we mostly implemented request/inform protocols).

The organizational model was implemented using the Moise library (Hubner et al., 2007). Each role was then implemented as agent and action classes from the Jason library (Bordini et al., 2007).

AGV Behavioral Model - Real AGVs are automatic transportation systems for transporting various loads. The type of AGV considered in this study requires a physical path painted on the floor in order to move. It can load a package from a given location and deliver it to a destination. The behavior of this type of AGV is represented by the state chart diagram shown in Figure 4, which comprises eight states, where an AGV is triggered by different incoming messages. In particular, each AGV is initially in a *waiting for mission* state. When new lorries arrive, the gate manager sends a broadcast message to all the AGVs. When an AGV receives this message, it asks the route planner for a path to reach its destination (*waiting for path*).

When an AGV receives the path (a list of waypoints to traverse), it starts to move along the path (*moving on path*). According to the particular area where an AGV is located, it can transit different states. An AGV is in the *picking* state or a *dropping* state when it is performing the actions required to take a pallet from a gate or to drop a pallet at a sorter, respectively. In the *gate freed* state, an AGV has picked up a pallet and it is waiting for the sorter place where it must go. Analogously, in the *sorting area freed* state, an AGV is waiting to continue its mission. If there are no other tasks to perform, an AGV transits into the *mission accomplished* state and waits for a parking zone.

It should be noted that the behavior of an AGV is not always the same and it depends on the stochastic delays introduced into some tasks. For example, the time required to pick up a pallet and leave a gate is influenced by a random delay in real situations, which may be caused by the difficulties an AGV experiences finding the correct position to pick a pallet. These stochastic delays may lead to different traffic congestion situations or different path allocations during simulation runs performed under the same conditions.

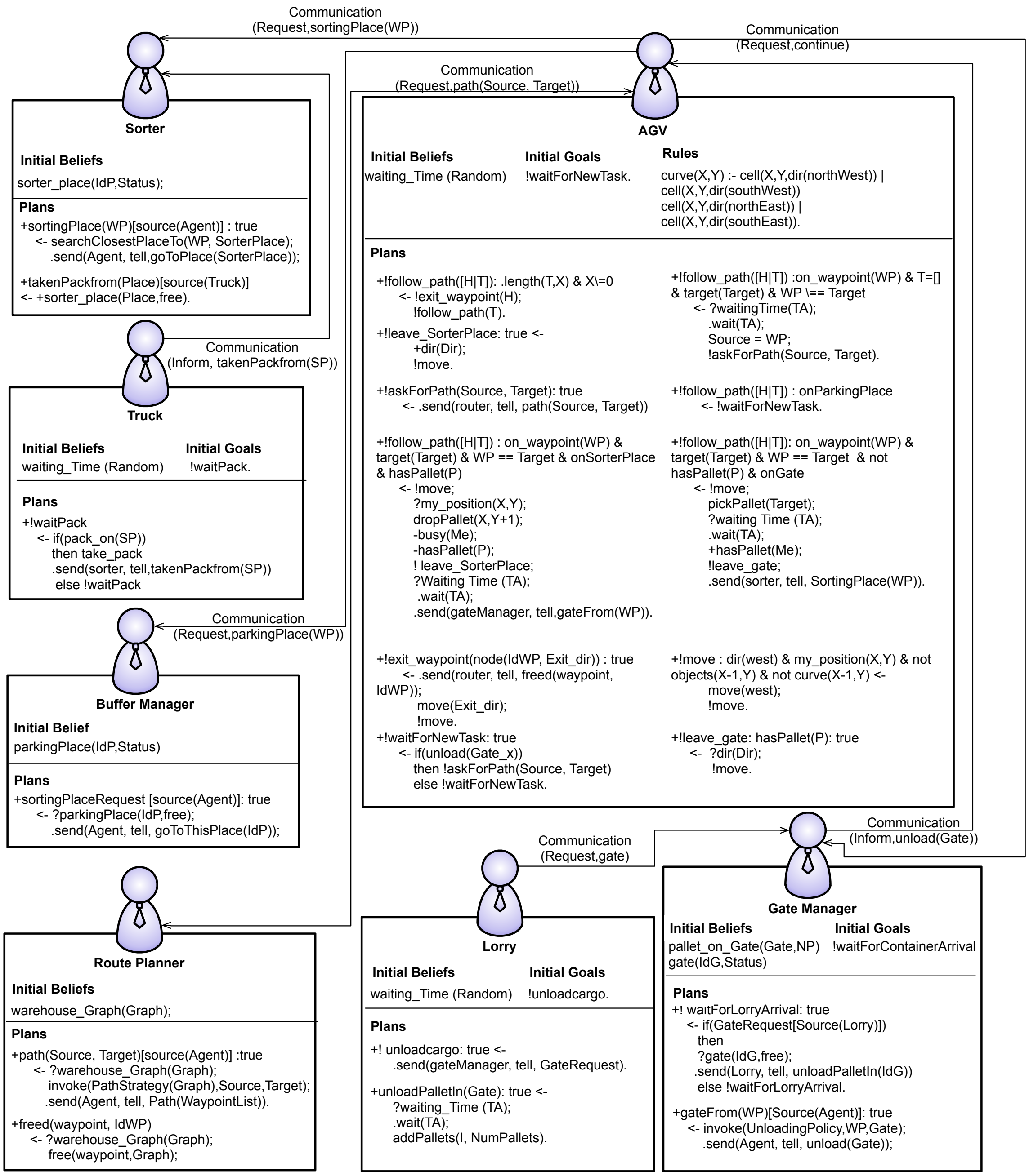


Figure 5: Detailed view of agent roles.

Experimental Setup

In the following, we use the term "factor" to refer to an explanatory variable manipulated during the experiment and "treatment" to indicate a combination of factor values. In this simulation study, we evaluated the performance of a warehouse according to the effects of several factors. In particular, our simulation study aimed to evaluate: 1) the impact of the physical configuration on warehouse productivity, 2) the performance of AGVs, 3) the impacts of different path reservation strategies, 4) the influence of different unloading policies, and 5) the impact of gate assignment. The experiment was designed to test five factors, i.e., layout, path reservation strategy, unloading policy, and the numbers of AGVs and gates assigned to incoming lorries. Each factor had different values (Table 1).

Simulation Parameters	*Layout*	*AGV*	*Unloading Policy*	*Path Reservation*	*Gate Assignment*
Value Range	1 - 3	1 - 15	NNP PP	1 Segments 2 Segments 4 Segments	23 Combinations

Table 1: Simulation parameters.

Each layout differed in terms of the locations of the structural elements, and the amounts and arrangement of the optical paths. In the simulation framework, the warehouse was represented as a grid map. Each cell could contain one or more structural elements, such as waypoints, path sections, and sorter positions. All of the elements were scaled according to the real dimensions (a cell represented 1 m^2).

Figures 6, 7, and 8 show the simulated warehouse layouts. Each layout contains five *gates* and one *sorting area* with 12 places. The specific details are as follows.

Layout 1: (Figure 6) The buffering area is in the internal part of the warehouse. Recharging zones are located to the right-hand side and the sorter is placed in the center of the lower side. This layout had two rings connecting the main areas. The rings have different directions for traveling. From left to right in Figure 6, the first three vertical lines (excluding those of the rings) denote the driving direction from the top to the bottom, whereas the remaining three lines are in the opposite direction. The two horizontal lines (excluding those of the rings) have right-left and left-right directions.

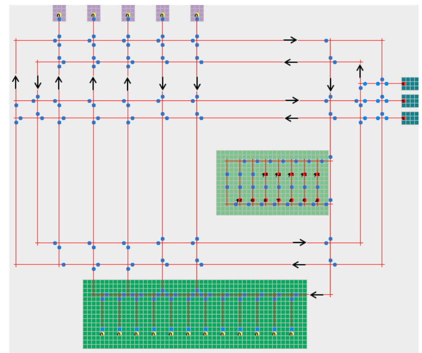


Figure 6: Warehouse layout 1.

Layout 2: (Figure 7) The buffering area is placed to the right-hand side of the warehouse and it is larger than that in the first layout. The sorter has been moved to the left in order to provide sufficient room for a greater number of recharging zones. The path lines are located so they form a grid with alternating directions of travel. The first vertical line is the driving direction from the bottom to the top, whereas the first horizontal line is from left to right.

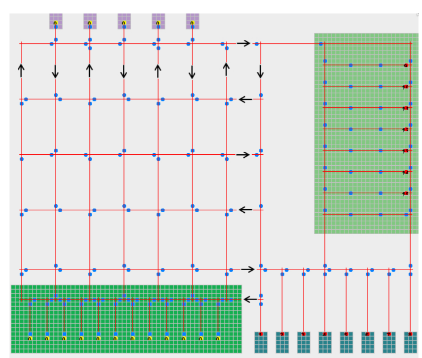


Figure 7: Warehouse layout 2.

Layout 3: (Figure 8) This layout has more northward paths than the previous layout. In this version, the old paths have a southward direction whereas the new ones have a northward direction in order to provide a return path to the sorter for AGVs that unload pallets from the gate on the left.

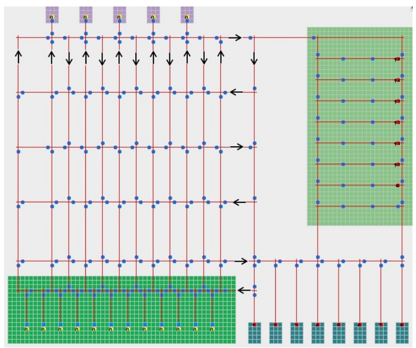


Figure 8: Warehouse layout 3.

Table 2 summarizes the settings for each warehouse layout.

Layout Parameters	*Layout 1*	*Layout 2*	*Layout 3*
Recharging Areas	3	8	8
Buffering Places	16	24	24
Waypoints	154	151	207
Path Segments	352	317	421

Table 2: Warehouse layout settings

The initial conditions used in the experiment were: *a)* AGVs are located on a waypoint for *recharging* or a *buffering area*; *b)* all gates are free and available; *c)* the sorter is empty and ready; *d)* all paths are available; *e)* the lorries arrive simultaneously; *f)* each lorry carries a container with 20 pallets; *g)* AGVs do not need to be recharged during the unloading operations; and

h) AGVs are assigned sequentially to gates to be unloaded (for example, in a simulation run with four gates and seven AGVs, six AGVs will be allocated to the first three gates, i.e., two for each, but only one will be assigned to the fourth gate).

In order to compare the simulation time with the actual time, the simulation time was scaled according to a scale factor (= 90.16). The scale factor refers to the ratio between the time required by a real AGV to cover a distance of 10.725 m at a speed of 1.5 m/s relative to the time required by a virtual AGV to perform the same task in the simulated environment.

The experiment comprised 2760 model runs. In each run, certain tasks were completed by the simulated entities. The time required to perform each task depended on the values of the factors. Thus, each model run was characterized by a different duration.

Due to time constraints, we did not perform a full factorial experiment. We divided the simulation tests according to the simulation objectives, as described in the following section.

Results and Discussion

In this section, we present the results of the simulation study. The results are discussed according to the particular issue addressed by each test.

A) Evaluation of the effect of the physical configuration on warehouse productivity.

In this subsection, we present our analysis and discussion of the results of an experiment that considered the three different warehouse layouts shown in Figures 6, 7, and 8.

The measure used to evaluating warehouse productivity is:

$$Throughput = \frac{UnloadedPallets}{ProcessingTime}, \tag{1}$$

where *UnloadedPallets* and *ProcessingTime* are the total amount of processed pallets and the elapsed time, respectively.

A subset of the simulation tests evaluated the influence of the physical configuration on warehouse productivity.

This subset comprised the results obtained by varying the AGVs, layout, and gate assignment, while fixing the values of the other factors according to the *two step path strategy* and *NNP unloading policy*. Thus, we

performed 1035 tests. The aim of this analysis was to determine the effects of variations in the AGVs and layout on the warehouse throughput. Two-way analysis of variance (ANOVA) was used to examine the effects of these factors on warehouse throughput.

The results of the statistical analysis are shown in Table 3, which is the classical ANOVA table obtained by two-way ANOVA, where *source* is the source of variability (i.e., the factors); *SS* is the sum of squares due to each source; *df* are the degrees of freedom associated with each source; *MS* comprises the mean squares for each source; *F* is the F-statistic, i.e., the ratio of the mean squares; and finally, *Prob>F* is the p-value, i.e., the probability that the F-statistic can take a value larger than the computed test statistic value. A p-value smaller than the significance level (usually 0.05 and 0.01) indicates that at least one of the sample means differs significantly from the others.

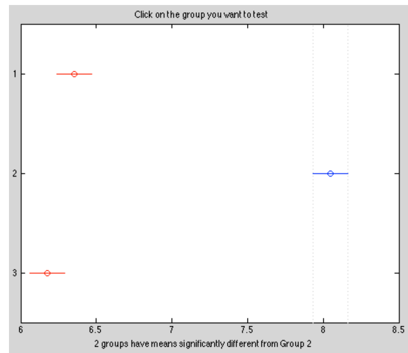
Source	SS	df	MS	F	Prob>F
Agv	101921.5	14	7280.11	142.45	0
Layout	18385.9	2	9192.95	179.88	0
Interaction	3229	28	115.32	2.26	0.0002
Error	50593.8	990	51.1		
Total	174130.2	1034			

Table 3: Results of the statistical analysis based on the warehouse throughput.

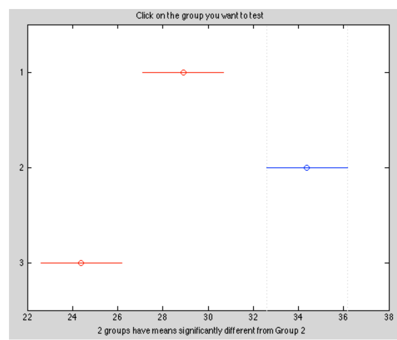
In the $Prob > F$ column in Table 3, the first two cells show the p-values related to the AGV and layout factors. The last cell shows the p-value related to the interaction between these factors. There was a statistically significant interaction (as expected) between the effects of the layout and AGV factors on the warehouse throughput (p = 0.0002).

Moreover, for the simple main effect of the layout factor when $AGV = 1$, $AGV = 6$, and $AGV = 15$ (Figure 9), we can see that the comparison intervals for *layout 1* and *layout 3* do not intersect with the interval for the *layout 2* when $AGV = 1$ and $AGV = 6$.

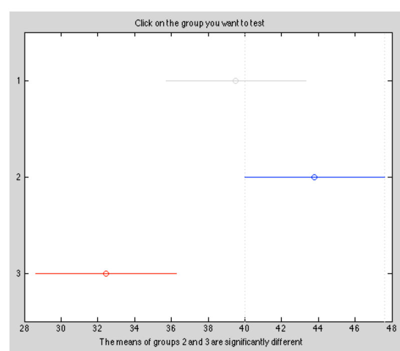
This lack of intersection indicates that *layout 2* had a mean that differed significantly from those of *layout 1* and *layout 3*, where this mean was higher than the others, particularly compared with *layout 3*, which obtained the worst result. By contrast, the simple main effects analysis showed that there were no differences between *layout 1* and *layout 2* when a warehouse employed 15 AGVs. However, *layout 1* and *layout 2* performed significantly better than *layout 3*.



(a) AGV=1

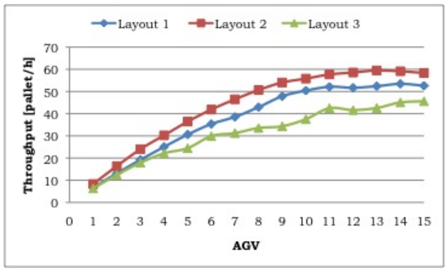


(b) AGV=6

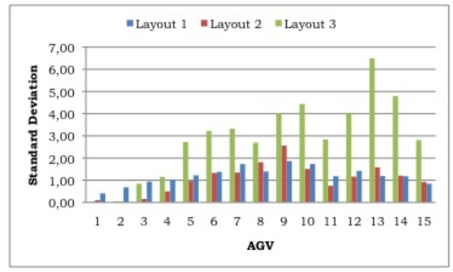


(c) AGV=15

Figure 9: Comparison of *layout 1*, *layout 2*, and *layout 3* for $AGV = 1$, $AGV = 6$, and $AGV = 15$.



(a) Mean throughput



(b) Standard deviation of throughput

Figure 10: Throughput and standard deviation of three different warehouse layouts **using the *two step path strategy* and *NNP unloading policy*.**

In addition to our statistical analysis of the simulation results, observations of the system's behavior while running can provide a deeper understanding of the numerical results. Thus, in order to make some practical observations, we considered a warehouse that operated with only three gates (the most common situation) and we discuss the results obtained. Figure 10(a) shows the mean warehouse throughput obtained by running the model, where the curves are labeled as *layout 1*, *layout 2*, and *layout 3* according to the layouts shown in Figures 6, 7, and 8, respectively. As we showed previously, the best performance was obtained using *layout 2*, but this result was not expected. We expected better performance using *layout3* due to the greater number of available paths toward the sorter, but this did not occur because the sorter places were not emptied sufficiently quickly. By contrast, after observing the simulations based on *layout 2* while running, we noted that the AGVs moved smoothly without path conflicts.

This was attributable to the homogeneous distribution of paths and the directions of travel.

Moreover, Figure 10(a) shows that the warehouse productivity also depended on the number of AGVs employed. The throughput using *layout 2* increased according to the number of AGVs and the maximum performance (i.e., 59 pallets per hour) was achieved using 13 AGVs, where further increases did not improve the performance. This is because the available paths were saturated, which blocked any traffic.

By contrast, *layout 1* had lower productivity due to the location of the buffer area in the middle of the yard (Figure 6). Indeed, when the AGVs had to deliver pallets to the sorter places positioned to the right, they had to turn around the buffer area, so they required more time to deliver the packages. The highest throughput value of about 53 pallets per hour was obtained with 14 AGVs. However, *layout 2* obtained higher productivity using a smaller number of AGVs.

Finally, *layout 3* (Figure 8) had the worst performance, although a greater number of paths were available between the gates and the sorter. In fact, in this layout, dedicated paths are added from a gate to a set comprising the nearest sorter places to prevent interference with the operations at the nearby gate.

The reduction in performance is due to the reservation policy employed at the sorter places and the time spent during unloading operations.

With a higher number of AGVs, the probability that the nearest sorter place is busy increases, which forces the system to assign another sorter place. This situation delays the unloading operations because the AGV follows a longer path and it interferes with the AGVs that operate on the adjacent gate. Thus, creating a circular path from a gate to the nearest sorter place does not obtain the expected improvement. The balance between the emptying time at the sorter place and the time required to complete a circular path is lost when the number of AGVs increases.

It should be noted that the bottleneck in the system is due to the longer time spent at the gate or the sorter. Only one AGV at a time can enter these places, which creates a traffic blockage. Thus, we evaluated the maximum number of AGVs that can be employed on a circular path without generating queues using the following equation:

$$\frac{T_{Gate} + T_{Go} + T_{Sorter} + T_{GoBack}}{N_{AGV_{Gate}}} \geq max\{T_{Sorter}; T_{Gate}\} \tag{2}$$

where:

- $T_{Gate} = T_{InGate} + T_{Load} + T_{OutGate}$ is the time required to enter the gate (T_{InGate}), to load a pallet (T_{Load}), and to leave the gate ($T_{OutGate}$);
- $T_{Sorter} = T_{InSorter} + T_{Unload} + T_{OutSorter}$ is the time required to enter the sorter place ($T_{InSorter}$), to unload the pallet (T_{Unload}), and to exit ($T_{OutSorter}$);
- T_{Go} and T_{GoBack} are the times required by an AGV to go from the gate to the sorter and vice versa, respectively;
- $N_{AGV_{Gate}}$ is the number of AGVs working at the same time on the same gate (a subset of the total number of AGV employed $N_{AGV_{Tot}}$).

In this particular case study using *layout 3*, the value of the numerator in the first term of Eq. (2) was about 9.25 minutes (real time) and $max\{T_{Sorter}; T_{Gate}\}$ is T_{Sorter} was approximately 5 minutes. Thus, this obtained $N_{AGV_{Gate}} \leq \lceil 1.85 \rceil$, which occurred (see Figure 10(a)) with $N_{AGV_{Tot}} < 4$.

Finally, we considered the standard deviation values using the three layouts (Figure 10(b)), where the results obtained using both *layout 1* and *layout 2* did not vary greatly from the average.

By contrast, the results obtained using *layout 3* showed that this configuration led to greater variability in the performance of the warehouse. This is because when the shortest path is busy, an AGV can choose among many alternatives and longer paths, and thus the time required to accomplish the operation increases. Therefore, it is more convenient to wait for an available nearby path rather than choosing an alternative longer path. Using *layout 2* (Figure 7), we can see that the differences are considerably smaller than those using *layout 3*, but the latter are comparable to those using *layout 1*. Thus, the choice of gate configuration did not have a great impact on the warehouse's performance using the first two layouts whereas it was very important with *layout 3*.

B) Evaluation of the performance by AGVs.

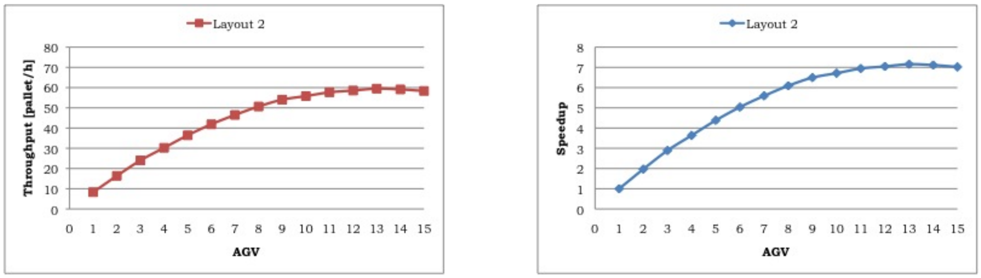
The *speedup factor* and the *slope* of the speedup curve were used as performance measures to determine a suitable number of AGVs for use in the warehouse. The *speedup* factor is defined as:

$$S(i) = T_{AGV=1}/T_{AGV=i}, \tag{3}$$

where $T_{AGV=1}$ and $T_{AGV=i}$ are the times required for unloading N pallets using one AGV and using i AGV, respectively.

Figure 11(b) shows the speedup curve for *layout 2*, which indicates that the speedup is not linear because the use of shared paths delays the warehouse operations. The slope value of this curve (Table 4) shows that there was a sudden drop above nine AGVs. The same table shows there was a decline in the warehouse's performance when using more than 13 AGVs. These results are useful because slope values may be employed by practitioners to define a decision point, as well as based on other considerations related to the cost of AGVs, their operational costs, and the gain obtained by reducing the unloading time.

For instance, let us suppose that the warehouse manager wants to buy some AGVs in order to automate the warehouse activities and



(a) Mean throughput

(b) Speedup factor

Figure 11: Throughput and speedup evaluations for a logistics warehouse using *layout 2*.

N°AGV	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Slope [%]	100	97	92	75	74	65	56	50	40	22	23	10	11	-4	-9

Table 4: Slope of the speedup function shown in Figure 11(b).

to obtain a throughput of about 45 pallets per hour. Based on the curves in Figure 11(a), they can deduce that the system is capable of handling 50 pallets per hour when using eight AGVs. By expanding the AGV fleet by one unit, the speedup factor increases from 6 to 6.5 (Figure 11(b)) and the throughput from 50 to 52 (Figure 11(a)).

Obviously, this increment should be compared with the additional cost for the purchase of a new AGV, as well as the income that can be obtained in the long-term and operational requirements in terms of the time required to unload containers. For example, a warehouse dealing with perishable goods needs to download all the containers within a tight time interval.

Moreover, Table 4 allows us to assess the contribution of each individual AGV and to fix a threshold value. For instance, the slope decreases suddenly from 50% to 40% after increasing from eight to nine AGVs, and it then continues to decline. Thus, eight AGVs may be the optimal number for the given warehouse layout that minimizes the importance of economical considerations.

This simulation study cannot solve problems related to marketing issues, but it can provide useful information to support decision choices.

C) Comparison of path reservation strategies.

Next, we analyze and discuss the results of the experiment related with using three different path reservation strategies in a typical working day. The metrics used in this comparison are the *throughput* (see Eq.1) and *efficiency*, where the latter is defined as:

$$E(i) = \frac{S(i)}{i} * 100, \tag{4}$$

where $S(i)$ is the speedup factor, which measures the efficiency of i AGVs working simultaneously. The efficiency of a single AGV is obviously 100%.

In this case, we chose a subset of simulation results to compare different path reservation approaches. We conducted an N-way ANOVA based on only three factors, i.e., AGV, strategy, and gate when layout =*layout 2* and policy=*NNP*.

The results of the statistical analysis are shown in Table 5. The first three entries in the *Prob* $> F$ column are the p-values for the main effects. The last three entries are the p-values for the two-way interactions between factors. The extremely low p-values (0 is an approximated value) indicate that the mean responses for the levels of each factor were significantly different. Moreover, we conducted

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
agv	31193.1	14	2228.08	6408.51	0
strategy	2534.8	2	1267.39	3645.33	0
gate	45.9	3	15.28	43.96	0
agv*strategy	1517.4	28	54.19	155.87	0
agv*gate	51.1	42	1.22	3.5	0
strategy*gate	5	6	0.84	2.42	0.0331
Error	29.2	84	0.35		
Total	35376.4	179			

Table 5: Statistical analysis of the effects of different path reservation strategies on the warehouse throughput.

a multiple comparisons test to verify the difference between the three strategies. Figure 12 shows a graphical representation of the multiple comparisons of the means for the simple main effects, which demonstrates that the *two step strategy* performed significantly better than the *one step strategy*, but there were no differences between the *two step strategy* and *four step strategy* when the warehouse employed $AGV < 7$. In addition, Figure 12 shows that using over seven AGVs in the *two step strategy* performed significantly better than the *four step strategy*. Figure 12 shows that the combination of $AGV = 7$ and the *two step strategy* had the same mean response values as the combination of $AGV = 7$ and the *four step strategy*, which indicates that the mean responses were not significantly different. By contrast, the combinations of $AGV = i, i > 7$ and *two step strategy* had mean response values that differed significantly from those of the others.

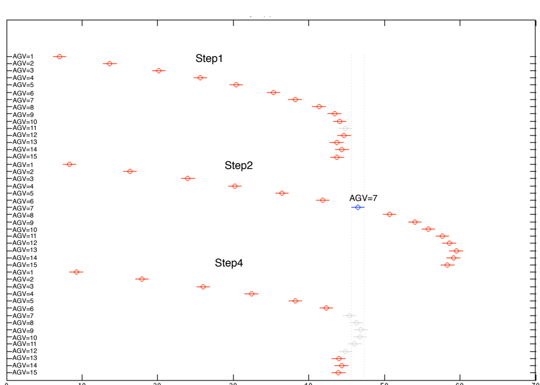


Figure 12: Multiple comparisons test based on the throughput.

The results of the statistical analysis based on efficiency are shown in Table 6. The previous analysis was also applied to these results.

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
agv	80170.5	14	5726.46	8720.19	0
strategy	2558.4	2	1279.2	1947.94	0
gate	33.9	3	11.3	17.21	0
agv*strategy	985.7	28	35.2	53.61	0
agv*gate	79.4	42	1.89	2.88	0
strategy*gate	10	6	1.67	2.55	0.0257
Error	55.2	84	0.66		
Total	83893.1	179			

Table 6: Statistical analysis of the effects of different path reservation strategies on the efficiency of AGVs.

We also conducted a multiple comparisons test to understand the effects of the interactions between the path reservation strategies and the number of AGVs on the efficiency of the AGVs. Figure 13 shows the results of these comparisons. All the combinations of $AGV = i, i < 4$ and $strategy = step1$, $AGV = i, i < 4$ and $strategy = step2$, and $AGV = i, i < 4$ and $strategy = step4$ had mean efficiency values that did not differ significantly. Using higher number of AGVs, the mean efficiency values with the *four step strategy* were significantly lower than those of the others.

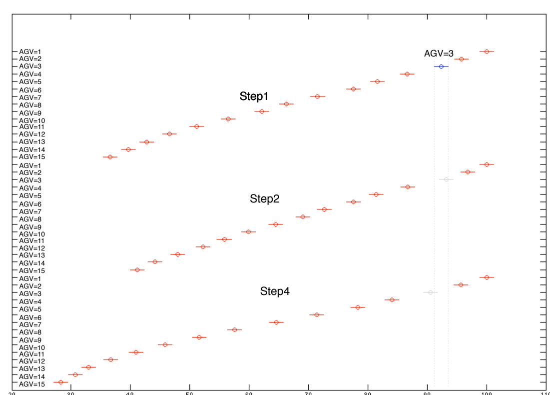


Figure 13: Multiple comparisons test based on efficiency.

We now consider the results obtained in terms of the run-time behavior of the system. Figure 14 shows the throughput with *layout 2* according to the different path reservation strategies in a warehouse working with three gates.

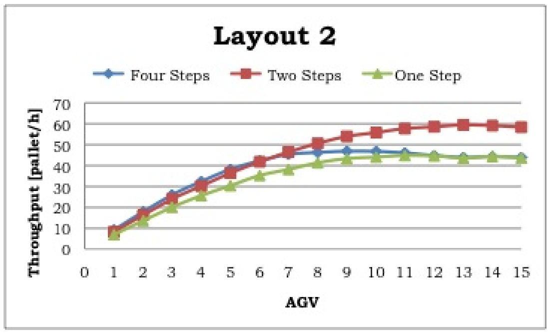


Figure 14: Throughput with different path reservation strategies in a warehouse using *layout 2*.

As shown previously, the best performance was obtained using the two step strategy and the worst using the one step strategy. This is because although the one step strategy releases paths quickly, it increases the AGV stop-start frequency to cause more delays.

By contrast, the stop-start frequencies and the resource release frequencies both decreased using four steps. Thus, several AGVs could not move because no paths were available to them. Figure 14 shows the performance of the one and four step strategies, which converge toward the same results with a high number of AGVs. This is because the negative effects that influence the different strategies have the same weight.

D) Comparison of unloading policies Next, we analyze and discuss the results of the experiment related to different unloading polices. Statistical analyses of the effects of different unloading polices on the warehouse throughput and AGV efficiency are shown in Tables 7 and 8, respectively.

Table 7 also shows that the unloading policies affected the warehouse throughput and there was an interaction effect between the number of AGVs and the different unloading polices strategies.

According to the results of a multiple comparisons test (Figure 15), we can see that there

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
agv	27287	14	1949.07	1066.61	0
strategy	2347.3	1	2347.35	1284.56	0
gate	32.1	3	10.7	5.85	0.002
agv*strategy	295.6	14	21.12	11.56	0
agv*gate	84.4	42	2.01	1.1	0.3792
strategy*gate	3.9	3	1.29	0.71	0.5531
Error	76.7	42	1.83		
Total	30127.1	119			

Table 7: Statistical analysis of the effects of different unloading polices on warehouse throughput.

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
agv	39646	14	2831.86	1340.65	0
strategy	955.3	1	955.31	452.26	0
gate	73.4	3	24.47	11.58	0
agv*strategy	305.4	14	21.82	10.33	0
agv*gate	100.6	42	2.4	1.13	0.3427
strategy*gate	32.4	3	10.79	5.11	0.0042
Error	88.7	42	2.11		
Total	41201.8	119			

Table 8: Statistical analysis of the effects of different unloading polices on the efficiency of AGVs.

was no difference between the NNP policy and PP policy when the warehouse employed one or two AGVs. The effect of the NNP policy on warehouse throughput was more significant than the PP policy when $AGV = i, i > 2$. For example, Figure 15 shows that the NNP policy performed better than the PP policy when AGV=3 and there was no difference in the warehouse throughput using the NNP policy when AGV=4 and using the PP policy when AGV=3. Moreover, when $AGV = i, i > 10$, $strategy = NNP$ differed significantly from all combinations of $strategy = PP$.

In terms of the system's behavior, this difference occurred because the AGVs traveled shorter distances. Moreover, using more than 12 AGVs, the performance decreased with the PP policy because the presence of many AGVs caused traffic congestion in the fullest gate.

In terms of efficiency, Fig.16 compares the results obtained using different unloading polices, which shows that there was no difference between NNP when AGV=6 and PP when AGV=4. We also found that the numerical results could lead to misinterpretations, where it appeared that it was more convenient to use the PP policy, but after considering the

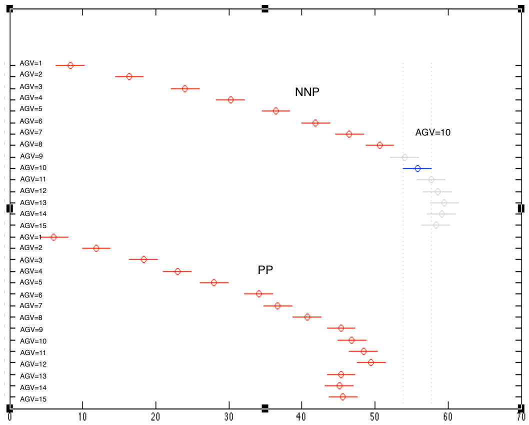


Figure 15: Multiple comparisons test of the effects of different unloading polices and numbers of AGVs on the throughput.

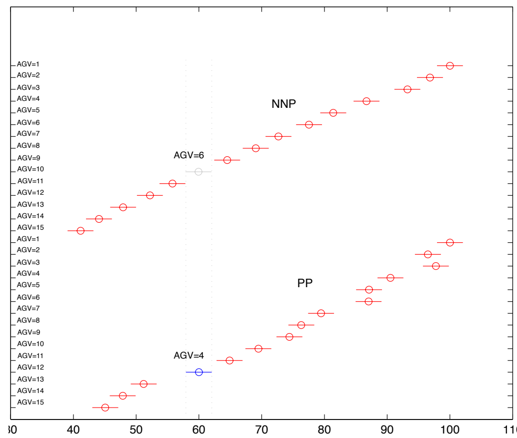


Figure 16: Multiple comparison test of the effects of different unloading polices and numbers of AGVs on the efficiency.

behavior of the system while running, this effect was attributable to the greater distance travelled by the AGVs when using the PP policy. In fact, the AGVs moved further but achieved less useful work because they travelled to more distant gates.

E) Impact of the assignment of docking platforms - Certain gates may be preferable to others inside a logistics warehouse, which usually occurs when they are located closer to areas of interest, such as the sorter area. Thus, we analyzed the impact of gate assignment on the warehouse throughput. We conducted a further series of tests (i.e., 540 tests) to evaluate the impact of the order of gate assignment on the warehouse performance. **These tests were conducted using layout =*layout* 2, policy=*NNP*, and strategy =*two steps*.**

In these tests, the system simulated the arrival of several containers during a typical working day.

In particular, we discuss the results obtained with four possible configurations using three docking platforms. These specific settings allowed us to test the behavior of the system when the employed platforms were adjacent or otherwise. In the first condition, we analyzed three different cases: the platforms employed were at the right (*{gate 1, gate 2, and gate 3}*), the left (*{gate 3, gate 4, and gate 5}*), or the center (*{gate 2, gate 3, and gate 4}*) relative to the sorter position (Figure 7). In these configurations, the AGVs contended for common paths. The second condition was represented by the configuration *{gate 1, gate 3, and gate 5}*, which was characterized by lower overcrowding of common paths. Thus, given the number of employed AGVs, the performance of the system was evaluated by varying the configurations of the docking platforms.

The labels on the bar graph in Figure 17 denote the configuration that obtained the best throughput relative to the number of AGVs employed. For example, when the number of AGVs employed was three, the best configuration was *{gate 3, gate 4, and gate 5}* (labeled as *G345* in Figure 17).

Figure 17 also shows the percentage throughput gain that could be obtained using the most favorable gate configuration.

For example, using configuration *{gate 3, gate 4, and gate 5}* and three AGVs, the warehouse performance improved by 11% compared with the worst case.

The advantage of each configuration compared with another also depended greatly on the number of AGVs employed because of the

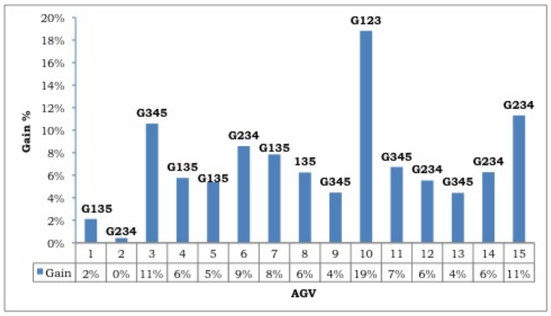


Figure 17: Percentage throughput with the best gate configurations when varying the number of AGVs.

unloading policy and the specific chosen layout selected, which forced the AGVs to prefer specific roads or sorter places.

These simulation tests allowed us to derive results that are relevant to warehouse managers in particular situations, such as a warehouse with a great workload within a defined time period.

In order to give a practical example, by analyzing the results in Figure 18(a) and Figure 18(b), which describe the performance of the system when the warehouse operates with 10 AGVs, a practitioner can deduce that the most profitable gate configuration for unloading the incoming containers is *G123*. In fact, this choice can improve the throughput by 19% compared with the minimal throughput in the system. Moreover, Figure 18(b) shows that in this specific case, all the gates are unloaded almost simultaneously, so the AGVs are distributed equally among the gates.

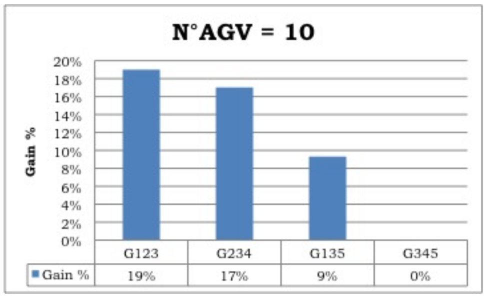
Furthermore, the results in Figure 18(a) suggest that it is possible to order the docking platforms so they are allocated according to the gain in productivity.

For example, a gate manager can choose to employ gate configuration *G123* to dock the articulated lorries, thereby obtaining the maximum possible throughput for the warehouse (19% better than the minimal productivity). If gate 1 is not accessible, then the manager can choose gate configuration *G234* with a loss of 2%. If both gate 1 and gate 2 are not available, then the warehouse will work at its minimal capacity.

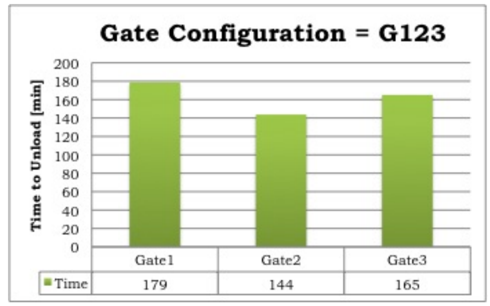
F) Lessons Learned - The simulations performed in this study illustrate issues related implicitly to the use of typical devices inside a logistics warehouse. In particular, a great constraint is represented by the use of optical lines for the movement of AGVs. Indeed, the design of optical guides limits the mobility of AGVs and thus the productivity of the overall system. This issue as well as the strategies employed for path reservation and unloading operations comprise an intricate system of interdependent variables. In terms of the warehouse layout design, we note that a peripheral position for the buffering area is preferable to a central one. In the scenarios considered, there was no storage of goods and the arrival of containers was continuous, so there were considerably fewer visits to the buffering area than the sorting area. Thus, by moving the buffering area along the perimeter of the warehouse, shorter paths to the sorting machine can be obtained, thereby decreasing the time required for the unloading operations. Moreover, the introduction of more optical guides will not always obtain the expected improvement. In fact, the presence of additional paths allows the sorting machine to be reached more easily but its limited processing capacity creates queues that block traffic.

We also note that the use of a rigorous safety policy can be disadvantageous in terms of the amount of useful work performed. Thus, it is necessary to make a trade-off between the safety levels required, the wear of AGVs, and the desired warehouse productivity level. Therefore, the safety criteria employed to prevent dangerous accidents must consider the distances among AGVs and their obstacle avoidance capacity.

In this study, our simulations demonstrated that the use of a less restrictive safety policy (obstacle avoidance, a short distance between two AGVs, and single step reservation) may allow more AGVs to move due to the availability of multiple free paths. However, this would also waste more AGV resources (the continuous stop-start behavior will consume both the



(a) Gain in productivity with different gate configurations.



(b) Time required to unload each gate under the most profitable gate configuration (*G123*).

Figure 18: Gain in productivity relative to the gate configurations and the time required to unload each gate under the most profitable configuration (*G123*) when 10 AGVs were employed.

AGV's tires and more power). By contrast, a strong safety policy (obstacle avoidance, long distance between two AGVs, and reservation of multiple steps) will decrease productivity but waste less AGV resources.

Conclusions

In this study, we performed a simulation-based study to support decisions regarding the physical configuration of logistics warehouses and their operational management. The warehouse model was based on a real-world case study and it is representative of a large number of logistics warehouses that use AGVs for goods transport.

The simulations analyzed the impact of various warehouse layouts and management strategies with different numbers of AGVs on the productivity of a logistics warehouse. This evaluation employed the following metrics: the throughput measured the warehouse productivity, the speedup factor determined the most affordable number of AGVs, and the efficiency metric evaluated the average number of AGVs used.

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