# An integrated simulation modelling approach for a warehouse 4.0

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# Abstract

In a progressively unstable business environment characterized by customers' demand challenging to predict, innovative solutions must be developed to respond to the growing need for flexibility in supply chain operations. In this scenario, the innovations of Industry 4.0 allow exploiting new methods for the development, management, and improvement of processes. Supply chain operations can significantly benefit from implementing one of these innovations, namely Warehouse automation, which is composed of automated retrieval and storage systems (AS/RS) and mobile robots (MR). This article contributes provides a hybrid virtual model based on Agent-Based Modeling and Simulation (ABMS) and Discrete Event Simulation (DES) paradigms of an integrated warehouse system, aiming to an ex-ante evaluation of the level of performance of the various logistic flows and the impact of operating parameters. The system into analysis consists of an automated warehouse with a maxi-shuttle-type translator, enslaved by mobile industrial robots and interfaced with a laboratory factory system equipped with an assembly station. Four experiments are carried out to analyze the warehousing system's performance by varying different parameters and design configurations. Results show that the model can determine the best design trade-off in terms of performance and is able to identify the bottlenecks of the system.


# 1. Introduction

The term Industry 4.0 refers to the fourth industrial revolution [1]. It was first used at the Hannover Fair in 2011, and it is still widely employed in Germany to indicate industry-related fairs, conferences, or call for public-funded projects [2]. The idea of Industry 4.0 shares common aspects with developments in other European countries, where it has been labelled differently, such as Smart Factory, Smart Industry, Advanced Manufacturing, or Industrial Internet of Things (IIoT) [3]. Since the first appearance of Industry 4.0, governments are proposing plans and strategies for industrialization and technological improvements. Meanwhile, also big companies are investing heavily in Internet-of-Thing (IoT) and Cyber-Physical Systems (CPS) related projects, experiments, or industrial applications [4].

The Industry 4.0 paradigm's relevance is notably in the logistic industry since it is becoming a driving factor for managing operations at warehouses and distribution centers. In fact, as noted by Taliaferro *et al.* [5], "*Warehouse-based stockpiling of inventory has been transforming into high-velocity distribution centers, which are increasingly considered strategic to providing competitive advantage. Industry 4.0 can aid the distribution center evolution, enabling adaptable, automated systems that can work with humans*". Therefore, warehouse automation lies at the forefront of every practical implementation of the Industry 4.0 paradigm in the logistics industry contexts. In this context, the main components of an autonomous warehouse are mobile robots (MR), lifts and a system of rails in the rack area called an automated storage and retrieval system (AS/RS) [6]. AS/RSs represent one of the major material handling solutions employed in warehousing contexts to store and retrieve finished products and parts [7].

Innovative technologies such as autonomous warehouses require a thorough evaluation by managers before investing significantly in the actual implementation. In this context, *ex-ante* performance analysis of an AS/RS is already a well-developed research field albeit mostly skewed towards analytic models [8–10].

Generally, in large, complex, and dynamic material flow and AS/RS systems the analytical evaluation may be lacking in acknowledging the interactions between the design and control decisions undertaken [11, 12]. This shortcoming opens up new possibilities for simulation studies to compare a significant number of design combinations and system configurations. In the era of Industry 4.0, computer simulation represents a powerful tool used in a broad spectrum of fields, including supply chain management, engineering, and manufacturing systems [13]. Simulation supports the ex-ante impact analysis of complex warehousing systems so to assess different configurations and parameters, as shown by Ekren [14]. For this reason, "*simulation is a key technology for developing planning and exploratory models to optimize decision making as well as the design and operations of complex and smart production systems. It could also aid companies to evaluate the risks, costs, implementation barriers, impact on operational performance, and roadmap toward Industry 4.0*" [15]. Application of simulation to real-world problems has proved its effectiveness in evaluating the design, performance, and problems of complex stochastic systems [13]. The recent exponential growth in computer power and technology performance has made possible the application of simulation to a system design stage and system optimization phases. Therefore, simulation-optimization approaches provide powerful decision-making methodologies able to incoroporate dynamic inputs and thus manage the complexity of industrial systems [16].

Moreover, autonomous warehouses do not operate in a vacuum. They are more often than not combined with human operators, composing a collaborative machine-machine and human-machine environment [17, 18]. One example of such collaborations is represented by the integration between an AS/RS for storage and retrieval and an MR-based system for material flows [19]. Existing literature proposes a narrow perspective of AS/RS as a stand-alone implementation, thus missing the necessary interactions between the AS/RS system and its warehouse counterparts.

This research contributes to bridging this research gap by adopting a multi-method simulation approach to model an integrated warehouse, material flow and human operating system to evaluate the impact of exogenous variables and consequent endogenous configuration decisions on its performance. Therefore, the remainder of this article is structured as follow. Section 2 proposes a review of the state-of-art regarding simulation applied to logistics and warehouse context to justify this study's scientific relevance. Section 3 consists of the description of the system into the analysis. Section 4 shows the simulation model's description, while Sect. 5 explores its usages and the experiments conducted. Section 6 proposes the analysis of the results of the various experiment conducted with the model, and Sect. 7 presents the conclusions of this study.

# 2. Research Background And Contribution

There are several simulation-based approaches available in the literature [15]. Within the context of Industry 4.0 and warehouses, the ones mostly employed are Discrete Event Simulation (DES), Agent-Based Modeling and Simulation (ABMS) and Hybrid Simulation (HS). DES consists of a set of techniques, which applied to the analysis of a discrete-event system, generates a model that exemplifies its performance. A discrete event system is a system in which at least one phenomenon of interest changes value or state at discrete points in time, instead of continuously with time [20]. In ABMS or Multi-Agent Systems (MAS) [15], the behavior of the system analyzed is not modeled directly; however, it emerges from the interactions of its constituent agents [21, 22], that is autonomous decision-making entities that individually assess their situation and take decisions based on a set of rules [23]. HS is also called multi-method or multi-paradigm simulation, and it consists of a combination of two or more simulation methods [24]. Hybrid simulation permits to better understand the complex system [25], and it is advantageous to develop more straightforward and more efficient models [26].

In literature, many examples of the application of these three simulation-based approaches may be found. DES has become a popular method to simulate actual operations and evaluate different scenarios through designing models of production systems, and support decision-making [27]. It finds application in facility layout design since it deals with the allocation of machines and departments and represents a relevant factor affecting manufacturing operations' effectiveness and efficiency [13]. A discrete event simulation has been employed to evaluate the performance and compare the analytical travel time models for a shuttle-based storage and retrieval system with aisle changing shuttle carriers [28, 29]. DES has also been developed to reproduce accurately many of the AS/RS settings observed in industrial contexts, building a model in which inbound and outbound flows are separated, as well as the physical and decisional components [11]. A computer simulation model of an AS/RS with rail-guided vehicles (RGVs) as material handling tool has been used to examine the operational logic of the entire system and determine the optimal number of vehicles, the utilization of the narrow-aisle crane and the maximum throughput of the system [30]. There are also examples of DES applied to modelling and simulating complex control algorithms of objects flows in the internal transport operations [31]. Discrete Event Simulation has also been employed in the study of different sorting systems [32] and the analysis and optimization of sorting strategies of logistics distribution centers [33].

Similarly, to discrete-event simulation, ABSM finds application in warehouses and logistics context. It has been demonstrated the ability of ABSM to support the understanding and quantification of congestion in a warehouse order picker system, providing more general insights than attainable using other modeling paradigms [34]. This approach has also been employed to evaluate the performance of a mini-load multi-shuttle order picking system, composed of a storage area, picking workstations and a loop conveyor to transport the product totes between the storage area and workstations [12]. Another application found in literature is the development of an agent-based model to study the retrieval time reduction of a list of products by choosing the best combination of storage and retrieval rules applied to an AS/RS fitted with a gravity conveyor [35].

Hybrid optimization/simulation modeling approach has been employed to design a distribution network considering the dynamics of clients and service time at each warehouse. The model developed was used to evaluate the best warehouses capabilities based on the level of service time [36]. Moreover, HS finds application in defining optimally integrated schedules for production and logistics processes along a global supply chain, where the combination of linear programming, DES and a numerical experiment has been used [37]. An HS model built integrating DES, and ABMS paradigms were employed to simulate the inbound logistics operation of a food hub, observe producers' scheduling behavior in different situations, and analyze the effectiveness of incentives policy addressed producers [38]. A hybrid model based on DES and System Dynamics has been developed to study the dynamics of passengers' logistics crossing between two cities to test the efficacy of this modelling approach to study complex logistics systems [39].

Concerning the state-of-art analysis, it seems that existing research regarding warehouses only focuses the attention on simulation-optimization of an automated part rather than the whole logistics system. Other studies apply simulation-based techniques to examine logistics networks from a more macro-level perspective. Additionally, a lack of research in Hybrid Simulation applied to an integrated warehouse system justifies this study. For this reason, the adoption of a multi-method simulation modelling approach based on DES and ABMS model and used to evaluate the impact of exogenous parameters and endogenous configuration decisions on the performance of the integrated system is proposed in this paper. Following the concepts and fundamentals of simulation modelling [40–45], the research pursued the following steps: a) the description of the system into the analysis; b) construction of a conceptual model c) translation of the conceptual model in a virtual model; d) simulation of different scenarios varying exogenous and endogenous aspects e) analysis of the results of the simulations.

# 3. System Description

The first step in simulation modelling is the system description, namely "*a description of the problem situation and the system in which the problem situation resides*" [43]. The object of this study is an integrated warehouse system to be installed in a university laboratory at the Politecnico di Torino, Italy. The warehouse system will be employed for storing a limited number of small components, which undergo light assembly operations to manufacture final products destined for shipment. Several auxiliary operations are also simulated in the warehouse system, ranging from simple picking to the creation of assembly kits for the main process of product assembly. Materials are collected in totes (plastic containers) and carton boxes to facilitate their movement. The warehouse is composed of an automated area, a kitting station, a picking station, two MRs, an inbound area, an assembly station, an outbound area and a general buffer of empty totes (Fig. 1).

The automated area (Fig. 2) is characterized by a maxi-shuttle that consolidates both the totes' horizontal and vertical movement. The automated area interfaces with the MRs through an input and an output conveyor dedicated to material handling. Moreover, this area includes a kitting station provided with a pick-to-light system and dedicated to the composition of kits intended for assembly. The kitting station is adjacent to the AS/RS and thus all parts are accessible from a single front, a design configuration

deemed to be beneficial for reducing order times [46]. Finally, there is a picking station employed in the manual preparation of orders destined for shipment.

The warehouse is operated through a triple layer management information system. The first layer is represented by the Warehouse Management System (WMS); the second layer consists of the Warehouse Control System (WCS), while the third layer is composed of the floor PLCs.

**Figure 1 The warehouse**

**Figure 2 Floorplan view of the automated area**

# 3.1. Description of the general flow of activities

Material flows, and the operations that characterize the warehouse are represented using a Unified Modeling Language (UML) activity diagram, a behavioral diagram used to describe aspects of a system (Fig. 3).

**Figure 3 Material flows and principal warehouse logics**

The inbound process starts at the reception of the components, and it is handled in a dedicated station. As this study focuses on the material flow and storage area's performance analysis, inbound operations such as labelling, inspection, and quality controls are not considered. At the inbound station, an operator puts the components into the totes and transfers the totes in a dedicated buffer, waiting to be successively moved to the automated area by a MR. For the put-away process, the warehouse management software monitors the rack shelf's availability, which includes the totes already transferring to the automated area. If there is a free warehouse position, the first available MR moves towards the buffer, loads the tote, and transfers it to the automated area. After that, the maxi-shuttle stores the tote in a free cell according to the system's allocation logic.

At the reception of a kitting order, the WMS executes a control to check if a worker is processing another order at kitting station. Additionally, it controls if there is at least one tote per component stored within the rack, to determine if it is possible to create a new kit. If the control is negative, the new order is added to a queue, and a supply order is emitted. If the control is positive, the order is accepted, and the kitting operation is performed. The maxi-shuttle retrieves the components totes and puts them in the gravity planes of the station.

Additionally, it retrieves an empty tote to be filled with the new kit. After the kitting operation, the kit can either be used directly for the product's final assembly or stored within the rack. In both cases, the maxi-shuttle handles the movement of the kit.

When an assembly order is received, the management software checks for at least one kit stored in the rack containing the components requested in the assembly order. If there are no readily available kits in storage, a kitting order is generated. In case of availability, the software sends a retrieval message to the

maxi-shuttle for retrieving the kit. The MR then transfers the kit to the assembly station, where an operator processes it. The manufactured products are then added to a dedicated tote, sent to the rack to be stored once their content is equal to a predetermined amount.

At the arrival of a picking order, the software monitors the presence of at least a tote stored in the rack containing the requested typology products. In case of availability, the maxi-shuttle retrieves it and transfers it to the picking station's gravity planes. On the other hand, an assembly order is automatically generated. An operator picks the products at the station and inserts them in an empty tote which is successively sent to the outbound area. As this study focuses on the performance analysis of the material flow and storage area, operations like packaging and shipment are not considered. Nevertheless, the buffer that simulates the outbound area is emptied once reached a predetermined amount of orders ready.

# 4. Model Description

The transition from system description to the conceptual model involves abstraction, which implies simplifying the real system and assumption about uncertain features [43, 47]. A conceptual model is the second step in simulation modelling. Its goal is to describe the real-world problem independent of a specific solution or instance [44]. Furthermore, it allows capturing the business domain with more formal means [41]. In this study, UML activity diagrams are used to formalize the fundamental aspects of the system. The model design process consists of the structured creation of objects intending to implement specific features, meaning the computer model's constructs (data, components, model execution, etc.) [40]. The computer environment selected to build the computer model is the simulation software AnyLogic, a multi-method simulation software employed in various industries, comprising supply chains, manufacturing, transportation, warehouse operations, business processes, and asset management [48]. AnyLogic provides libraries, industry-specific tools, and data analysis instruments that allow the creation and study of models at different detail levels.

# 4.1. Materials handled

As previously mentioned, the warehouse is employed to store various components contained in totes and boxes. For simplicity, only one container type and three components are taken into consideration. These components differentiate from each other via some attributes summarized in Table 1.

**Table 1 Component attributes**

The three components combine for three different products manufactured through light assembly operations. The attributes of the products are shown in Table 2.

**Table 2 Product attributes**

Since the automated area manages empty totes, kits, components, and products, an allocation logic is needed to differentiate the rack areas in relation to the items stored. In particular, it is assumed here that:

- The empty totes are stored on the side of the rack closer to the output conveyor;
- The completed kits are located between the middle of the rack and the output conveyor;
- The totes containing the components are situated between the middle of the rack and the picking station;
- The assembled products are stored on the opposite side of the rack in relation to the empty totes near the picking station.

Despite the differentiation of storage area, in every case a storage level is firstly filled completely before changing storage position, that is the totes are stored in height before moving along the rack.

Another aspect considered is material flow management. It consists of directing and controlling the sequence of activities from the supply of raw materials to final products distribution. It permits to balance the material flows and prevent any block of the system. It controls space availability within the rack to guarantee the possibility to stock another tote and the capacity of conveyors and machinery to value the chance to transport the containers. Without material flow management, the system would fall into errors like a collision of totes, a block of the maxi-shuttle, or congestion of flows.

# 4.2. Processes

To formalize the fundamental aspects, the system's processes introduced in Fig. 3. are further explored through UML activity diagrams. As an example, the activity diagram of the kitting process is shown in Fig. 4.

Within the AnyLogic simulation platform, processes are modelled in the form of flowcharts through the library blocks offered by the software. The flowchart approach represents the DES portion of the model. For example, the translation of the activity diagram of the kitting process in AnyLogic language is observable in Fig. 5.

**Figure 4 Kitting process activity diagram**

**Figure 5 Kitting process flow chart in AnyLogic**

# 4.3. Agents

A hierarchical structure distinguishes AnyLogic models. Each agent may encapsulate other agents at various level of depth, generating a structure composed of a tree of agents with different ramifications. The highest-level agent is called the top-level agent. It corresponds to the roots of the tree of agents and represents the model's highest level of abstraction. Any possible agent included in the top-level agent generates a lower level of abstraction. This peculiarity allows building a model at any level of detail desired and eventually hiding an object's particular complexity. Besides, it confers an adequate level of

flexibility to modelling in terms of the structure of the agents' model and nature. The hierarchical structure of the model assumes the shape showed in Fig. 6.

**Figure 6 Hierarchy tree of agents in the model**

In the model, the more complex agent is the one that reproduces the maxi-shuttle. It is composed of two agents: a) Crane, which simulates the column and the horizontal movement of the machine; b) Arm, which simulates the loading device and the vertical movement of the machine.

Its behaviour is conferred by two state charts, one for agent Crane (Fig. 7) and one for agent Arm (Fig. 8), while the storage, retrieval and transfer operations are triggered by the generation of the third agent Task.

**Figure 7 Crane state chart**

**Figure 8 Arm state chart**

## 4.4. Model calibration

The integrated warehousing system model is characterized by a set of parameters with specific values (Table 3). Some of them have been extrapolated from the specifications of the system, while others have been estimated based on similar solutions found on internet and companies' websites. Additionally, the processing time of the kitting, assembly, picking, and inbound processes was hypothesized concerning operators' operations.

**Table 3 Model calibration**

# 5. Simulation

The goals of the simulation of the hybrid DES-ABM model are several, namely:

1. Identify the bottlenecks of the system;
2. Assess the utilization rates of the main processes and resources;
3. Evaluate cycle times and estimate the throughputs;
4. Propose an optimal design solution.

To achieve these objectives, four scenarios were simulated. The first scenario refers to the baseline scenario (*Baseline*) described in Chap. 4. The second scenario considers the variation of external and internal kitting, assembly and picking demand rates (*DemandRates*), to stress the system under different demand conditions. The third scenario involves layout changes of the elements outside the automated area (*LayoutChanges*). As shown in Fig. 9, another assembly station is added to the environment, and its buffer is doubled, to ensure a greater volume of work for both stations.

Furthermore, the presence of another operator is assumed. The assembly station's position is switched with one of the buffers of empty totes, which is moved near the inbound station. The MR home is slightly

displaced in front of the automated station.

**Figure 9 Modified layout**

The last scenario maintains the layout variations of the third scenario, but it includes the increment of the picking process priority and the introduction of a scheduling algorithm for picking orders (*LayoutChanges + ProcessChanges*). Table 4 shows the rates of input values in the four scenarios.

**Table 4 Rates input values**

To compare the simulation results, a set of Key Performance Indicators (KPIs) have been identified, which can be grouped into two categories: productivity and time (Table 5). Regarding productivity, three KPIs have been estimated, namely utilization, Work in Progress (WIP) and throughput. Concerning time, two KIPs have been considered, that is cycle time and order time. Cycle time represents the time between the moment in which an order is being processed by the model and its final execution. In contrast, order time adds the order waiting time (i.e. between order reception an order processing) to the cycle time.

**Table 5 Key performance indicators**

# 6. Analysis Of Results

In this section, the results of the various simulations are described and analyzed (Table 6).

**Table 6 Scenario results**

Comparing the four scenarios in Fig. 10, it is possible to observe that the MRs utilization increases in each scenario. In this sense, the MR fleet does not represent a bottleneck of the system. Regarding the maxi-shuttle, the utilization rate enhances in each scenario, reaching a peak of 28.2%. Regarding the different stations, while the inbound, kitting and picking stations reach very low utilization levels in all the scenarios, the assembly station seems to be the warehouse's critical process due to the highest utilization rates in all the scenarios. In fact, assembly 1 utilization fluctuates from 64.6–69.6%, reaching a peak of 74.8% in *DemandRates*. With the introduction of assembly 2, the total workload is absorbed by the second station, which shows an increment in utilization by 23.8% moving from *LayoutChanges* to *LayoutChanges + ProcessChanges*. Concerning the rack, the highest utilization rate is reached in *LayoutChanges*, while the lowest in *LayoutChanges + ProcessChanges* 4. This last value is due to the higher material turnover caused by all the adjustments made during simulations.

**Figure 10 Utilization rate**

Focusing the attention on cycle and order times (Fig. 11), it is possible to notice that the KPI of the maxi-shuttle does not show alarming values and significant variations in the four scenarios. A low variation in cycle times related to a greater difference in order times is observable regarding kitting orders. This is because transferring and processing times do not change significantly, while waiting time presents some

fluctuations. Since the assembly process represents the most critical aspect of the whole system, its KPIs show great variations caused by the modification done in the various scenarios. With the increment of demand rates between *Baseline* and *DemandRates*, the cycle and orders times increase significantly, amounting to a 39.48% and 36.40% spike respectively. The introduction of a second assembly station generates the best values for these KPIs. Raising the demand rates in *LayoutChanges + ProcessChanges* causes another increment in cycle and order times by 33.91% and 30.39%. Concerning picking orders, the increment in demand rates causes a little increase in order time values. In terms of cycle and order time, *Baseline* represents the best scenario for the picking process due to negligible waiting times, while the worse scenario is *LayoutChanges*. The bad performance, in this case, might be caused by the greater number of supplies and kitting orders that have to be handled by the same resource assigned to the picking process. Furthermore, the split of assembly orders between the two stations may cause an increase in processing time before the completion of a tote at assembly stations and its transfer to the rack.

**Figure 11 Cycle and order times**

Regarding the WIP, the KPI improves moving from the *Baseline* to the other three. However, while the results for most processes are reasonably stable from the *DemandRates* onward, the assembly process suffers from large fluctuations in terms of WIP. The value of WIP for the assembly process falls abruptly by 90.51% during *LayoutChanges*, due to the introduction of the second assembly station. With the growth in demand rates between *LayoutChanges* and *LayoutChanges + ProcessChanges*, the WIP of the picking station increases by 101.04%.

**Figure 12 Average WIP**

Finally, throughput per hour shows a general improvement from the *Baseline* as well, especially for the maxi-shuttle operations. The only decrease in this KPI is observable for the maxi-shuttle and kitting operations between *LayoutChanges* and *LayoutChanges + ProcessChanges*, due to the picking orders scheduling and modified priorities introduced in *LayoutChanges + ProcessChanges*, which additionally lead to a slight improvement in picking orders processed per hour.

**Figure 13 Throughput per hour**

# 7. Conclusions

This paper proposes a novel hybrid model for simulation and optimization of an integrated warehouse system composed of an AS/RS system served by MRs, including manual operations such as light assembly, kitting and picking. The hybrid model was used to analyze the system's performance in different conditions, find an optimal design solution to be implemented, and understand where the major criticalities of the system reside. Considering the various results, the last scenario simulated represents the best trade-off scenario tested.

All the scenarios show relevant aspects of the system at hand. Firstly, it has been demonstrated that the bottleneck of the entire system resides in the assembly process. This problem also has negative consequences on the other processes, which function at under-capacity levels. Secondly, simulations illustrate which parts of the warehouse do not represent a critical point: inbound and kitting stations. The maxi-shuttle and MRs have a low level of utilization, which suggests that they do not represent the system's bottlenecks. Thirdly, all the scenarios reveal which aspects of the warehouse could potentially present future issues. For instance, the picking process may suffer considerable complications. Particularly, when the products stored within the rack terminate, picking orders may wait a long time before they can be processed. This is due to a low level of replenishment of products assembled.

Additionally, it is important to observe that some assumptions and simplifications were made during the abstraction process. Various elements can cause a deviation between the performance of the real system and the virtual one. Firstly, no breakdown of the machinery and maintenance have been introduced within the model. Failures generally occur in real systems and maintenance procedures are always present. Secondly, no fluctuation in demand rates has been considered. As a matter of fact, in real-world instances, external demand is always influenced by variations. Thirdly, no quality control processes have been taken into account during the construction of the model. Quality controls influence the system's functioning in terms of resource availability, time, rejections, and errors detection.

In conclusion, it is possible to state that the results obtained are positive and represent a good starting point for further and deeper analysis. Interesting research points concern the validation process of the model and the critical aspects found during simulations and showed in this research. In this regard, the model can envision the introduction of collaborative robots for the light assembly process, which might determine more precise, smooth and quick processing times. Moreover, a development perspective for the medium term may foresee the realization of a digital shadow, that is the unidirectional, automatic, and real-time connection of the physical space and the virtual one through a cyber-physical system. In a long-term perspective instead, it is possible to evaluate the integration of bi-directional information flow and artificial intelligence algorithms to create a complete digital twin, able to generate information automatically and establish the reciprocal connection between physical and virtual systems.

# Declarations

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## Conflicts of interest/Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

## Availability of data and material

The computer model is available upon request.

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# Tables

Table 1 Component attributes

| Attribute | Description |
|---|---|
| Type | Unique code that identifies the component (C1, C2, C3) |
| Color | Attribute to allow for visual representation during computer simulations |
| Batch size | Quantity of component supplied |
| Max tote | The maximum quantity of components that can be inserted in a tote |
| Order point | Stock quantity under which a supply order is emitted |

Table 2 Product attributes

| Attribute | Description |
|---|---|
| Type | Unique code that identifies the product (P1, P2, P3) |
| Color | Visual attribute to support during computer simulations |
| Number of C1 | Number of components C1 to create the kit/assemble the product |
| Number of C2 | Number of components C2 to create the kit/assemble the product |
| Number of C3 | Number of components C3 to create the kit/assemble the product |

Table 3 Model calibration

| Category | Parameter | Value |
| --- | --- | --- |
| Rack | Number of cells per level | 12 |
| | Levels | 6 |
| | Deep positions | 1 |
| Maxi-shuttle | Max travel speed | 6 m/s |
| | Max lifting speed | 3 m/s |
| | Loading/unloading fixed times | 3 s |
| Conveyor system | Capacity input conveyor | Three totes |
| | Capacity output conveyor | Three totes |
| | Speed | 0.5 m/s |
| | Delay transfer table | 1.5 s |
| Kitting | Capacity station | One tote |
| | Capacity gravity planes | Three totes |
| | Process time | ∼ triangular (9.5, 11.5, 14) s |
| Picking | Capacity station | One tote |
| | Capacity gravity plane | Six totes |
| | Process time | ∼ triangular (11.5, 14, 17) s |
| Assembly | Capacity buffer | Four totes |
| | Capacity station | One tote |
| | Process time | ∼ triangular (180, 240, 300) s |
| Inbound | Capacity buffer | Twenty boxes |
| | Capacity stat | One box |
| | Process time | 5 s |
| Outbound | Buffer capacity | Six totes |
| MR | Fleet | Two vehicles |
| | Maximum speed | 1.5 m/s |
| | Acceleration | 1 $m/s^2$ |
| | Deceleration | 1 $m/s^2$ |
| | Turn radius | 520 mm |

| | | |
|---|---|---|
| | Minimum distance to an obstacle | 50 mm |
| | Loading/unloading fixed times | 3 s |
| Resources | Number | Two operators |
| | Walking speed | 1.25 m/s |

Table 4 Rates input values

| # | Scenario | Kitting rate [ops/h] | Assembly rate [ops/h] | Picking rate [ops/h] |
|---|---|---|---|---|
| 1 | *Baseline* | 13 | 12 | 8 |
| 2 | *DemandRates* | 20 | 12 | 20 |
| 3 | *LayoutChanges* | 20 | 12 | 20 |
| 4 | *LayoutChanges+ProcessChanges* | 20 | 20 | 20 |

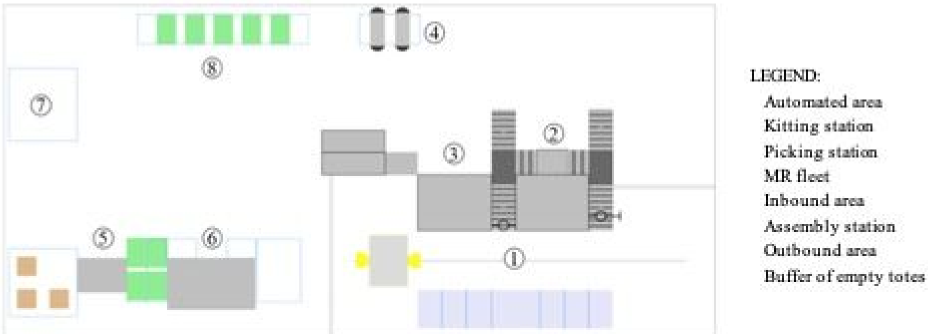
Table 5 Key performance indicators

| KPI | Description |
|---|---|
| Utilization | Percentage of time in which a resource is occupied. In case of rack, percentage of space occupied by items within the rack. |
| Cycle time | Cycle time of a process |
| Order time | Order time of a process |
| Average WIP | Average WIP of a process |
| Throughput | Number of operations / orders completed per hour |

Table 6 Scenario results

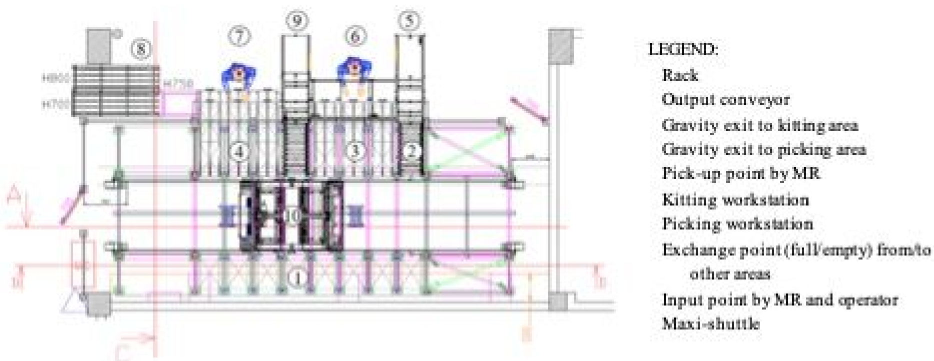
| Category | KPI | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 |
|---|---|---|---|---|---|
| Utilization [%] | MRs | 14.4% | 20.6% | 22.4% | 25.2% |
| | Maxi-shuttle | 14.6% | 22.8% | 27.0% | 28.2% |
| | Inbound station | 13.0% | 2.0% | 2.2% | 2.0% |
| | Kitting station | 5.4% | 7.6% | 9.2% | 7.6% |
| | Picking station | 2.0% | 7.6% | 7.6% | 8.4% |
| | Assembly station 1 | 64.6% | 74.8% | 51.6% | 69.6% |
| | Assembly station 2 | - | - | 38.0% | 61.8% |
| | Rack | 44.2% | 48.0% | 54.2% | 38.4% |
| Cycle and order times [s] | Mini-load cycle time | 8.00 | 8.11 | 8.62 | 8.46 |
| | Kitting cycle time | 24.78 | 25.78 | 27.44 | 27.18 |
| | Kitting order time | 30.35 | 59.41 | 51.84 | 46.37 |
| | Assembly cycle time | 406.58 | 567.10 | 337.08 | 451.39 |
| | Assembly order time | 453.06 | 617.99 | 357.17 | 465.70 |
| | Picking cycle time | 26.79 | 26.46 | 27.66 | 26.24 |
| | Picking order time | 26.90 | 33.05 | 62.32 | 58.12 |
| Average WIP [n° of items] | Maxi-shuttle | 0.18 | 0.28 | 0.39 | 0.38 |
| | Kitting | 0.14 | 0.40 | 0.40 | 0.38 |
| | Assembly | 1.45 | 2.93 | 1.54 | 3.09 |
| | Picking | 0.05 | 1.16 | 1.23 | 1.28 |
| Throughput per hour [ops/hour] | Maxi-shuttle | 74.33 | 119.69 | 144.31 | 141.48 |
| | Kitting | 11.70 | 18.18 | 23.50 | 19.37 |
| | Assembly | 6.41 | 7.40 | 7.75 | 10.12 |
| | Picking | 3.57 | 13.72 | 15.18 | 22.07 |

# Figures




## Figure 1

The warehouse




## Figure 2

Floorplan view of the automated area

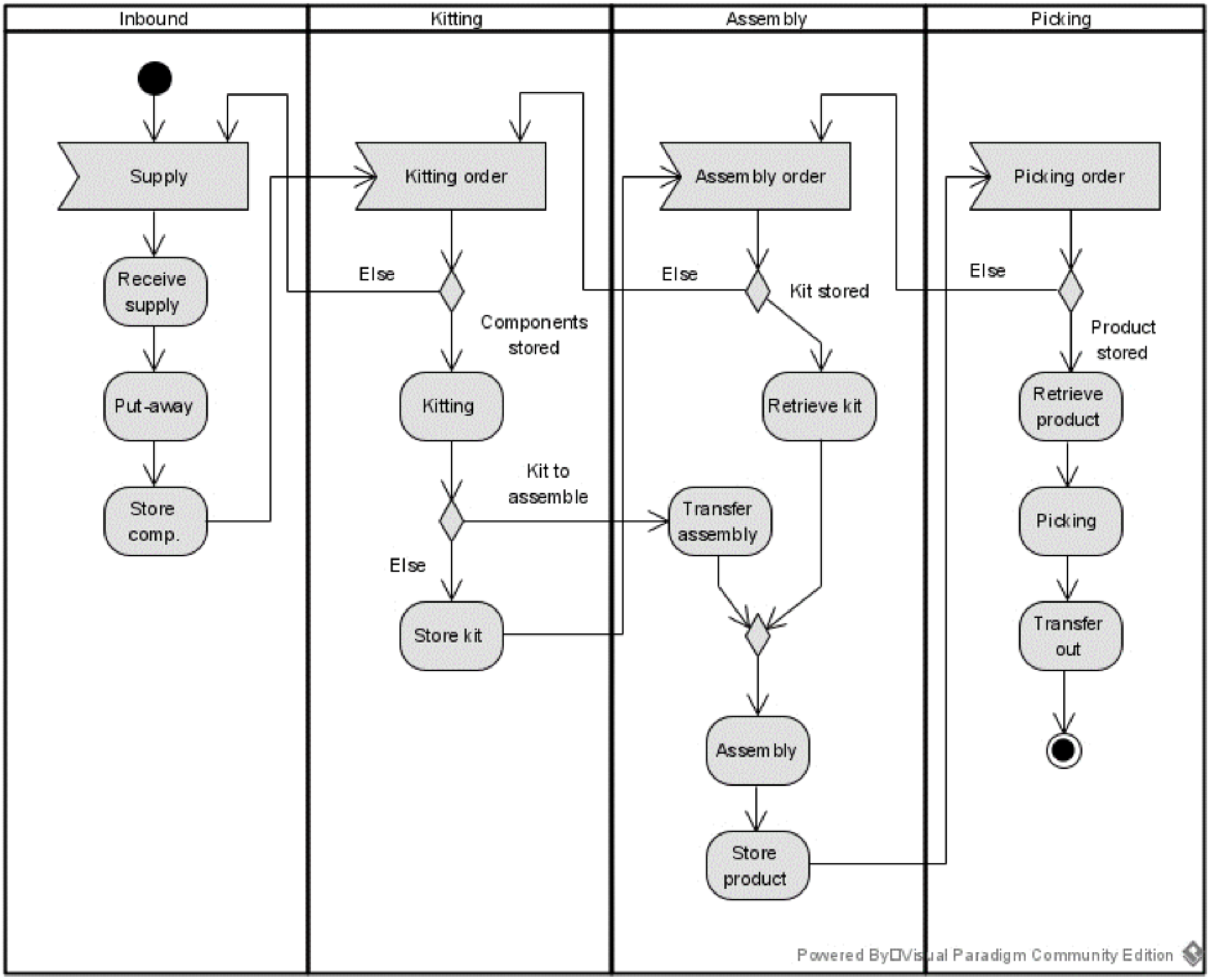
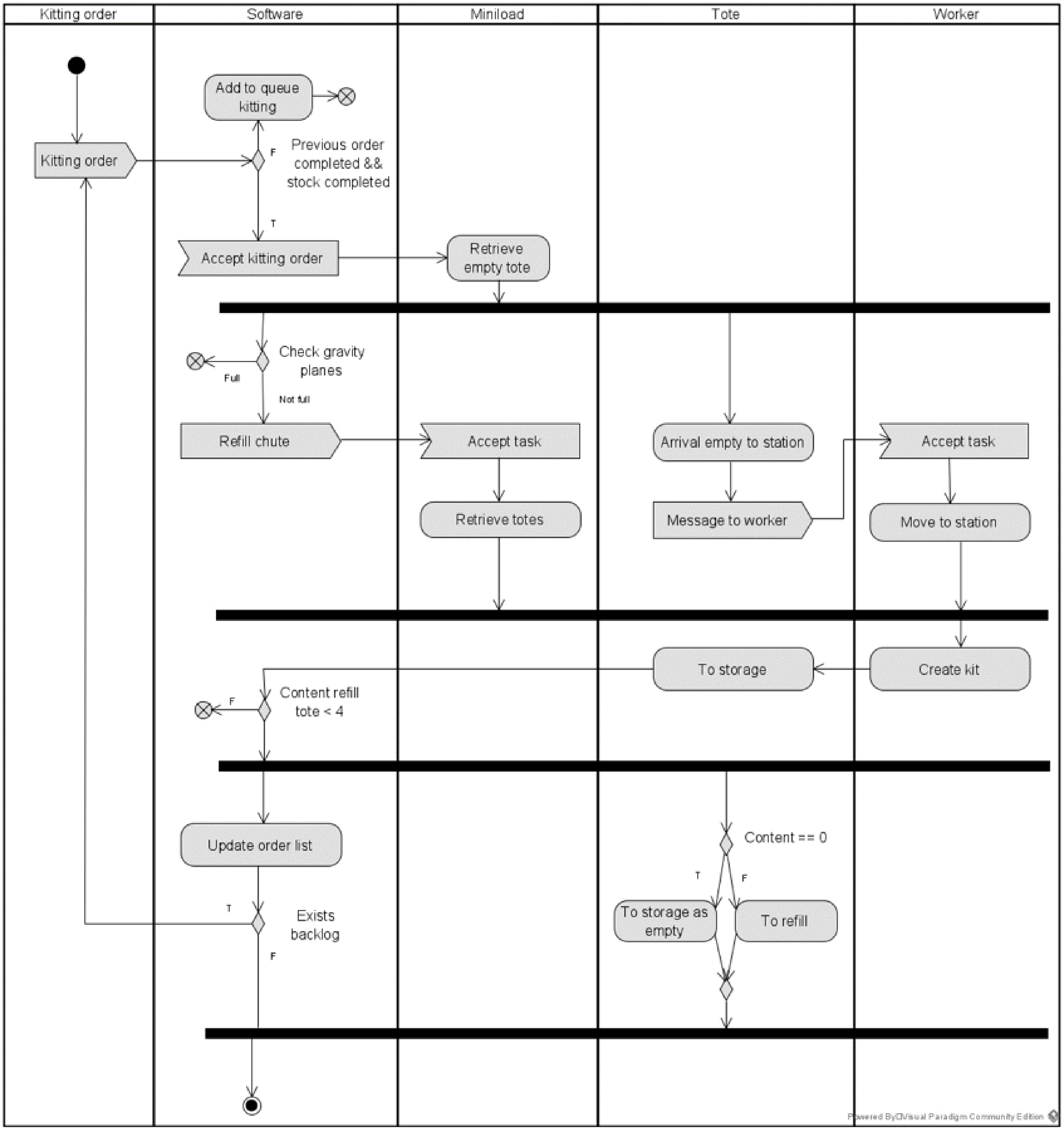



**Figure 3**

Material flows and principal warehouse logics




## Figure 4

Kitting process activity diagram

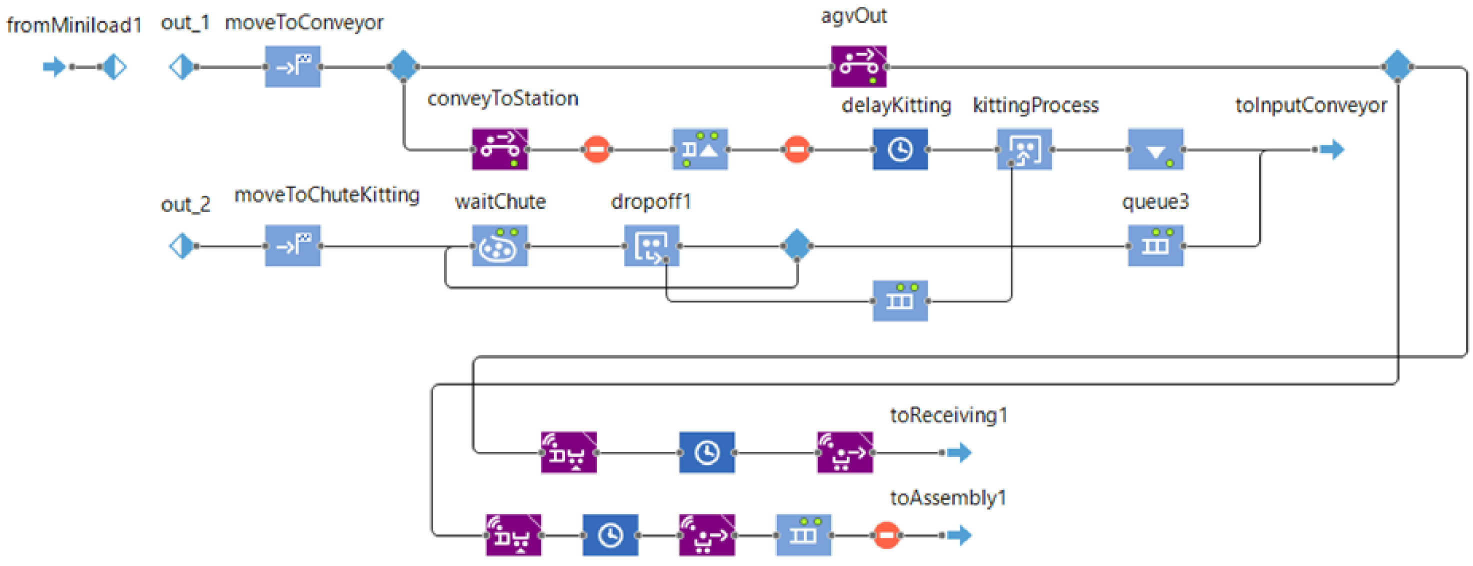



**Figure 5**

Kitting process flow chart in AnyLogic

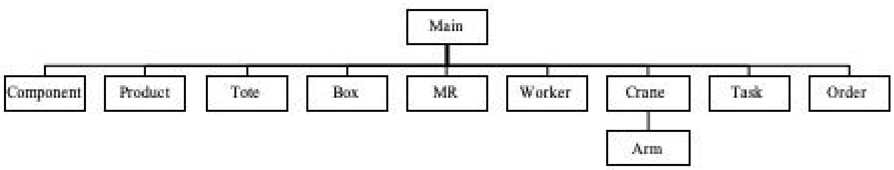
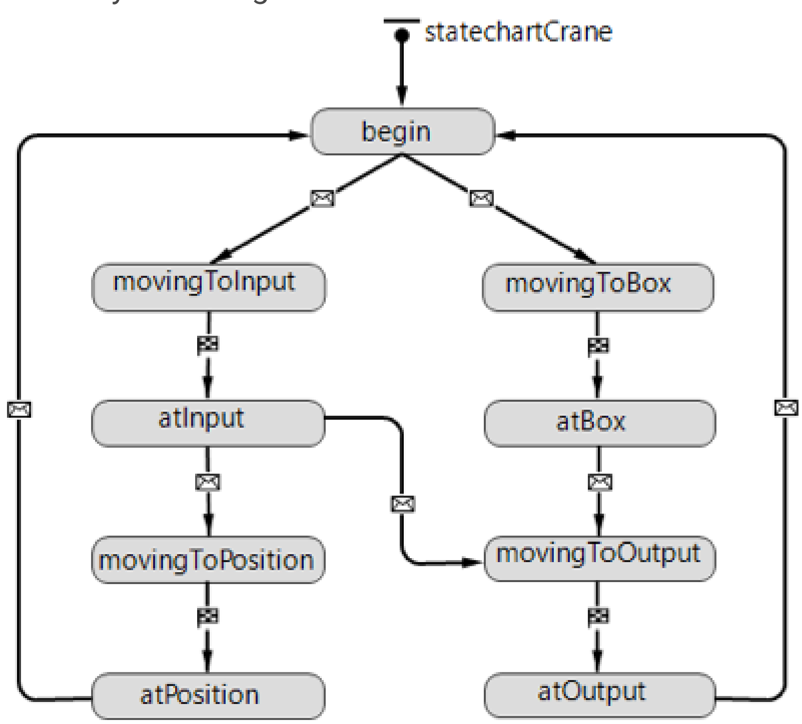


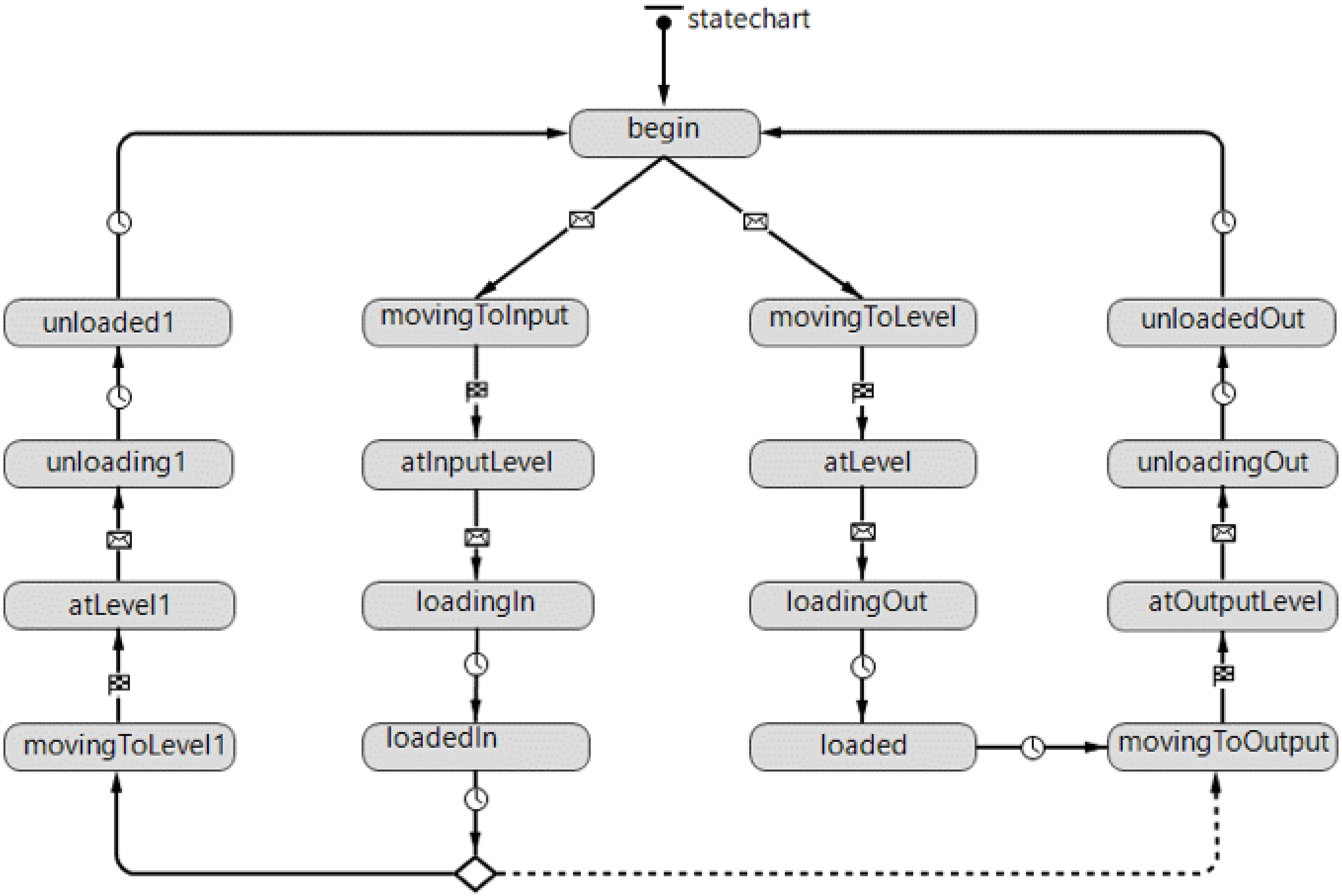

**Figure 6**

Hierarchy tree of agents in the model



### Figure 7

Crane state chart




### Figure 8

Arm state chart

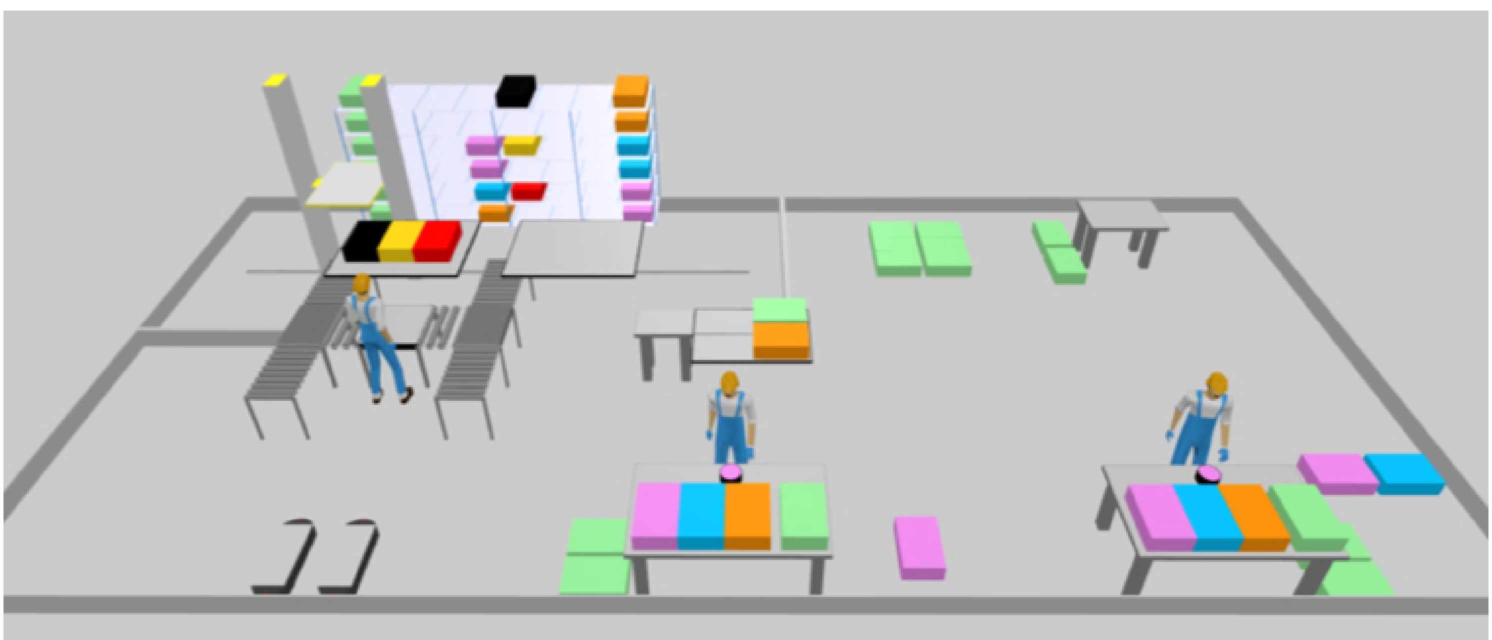


**Figure 9**

Modified layout

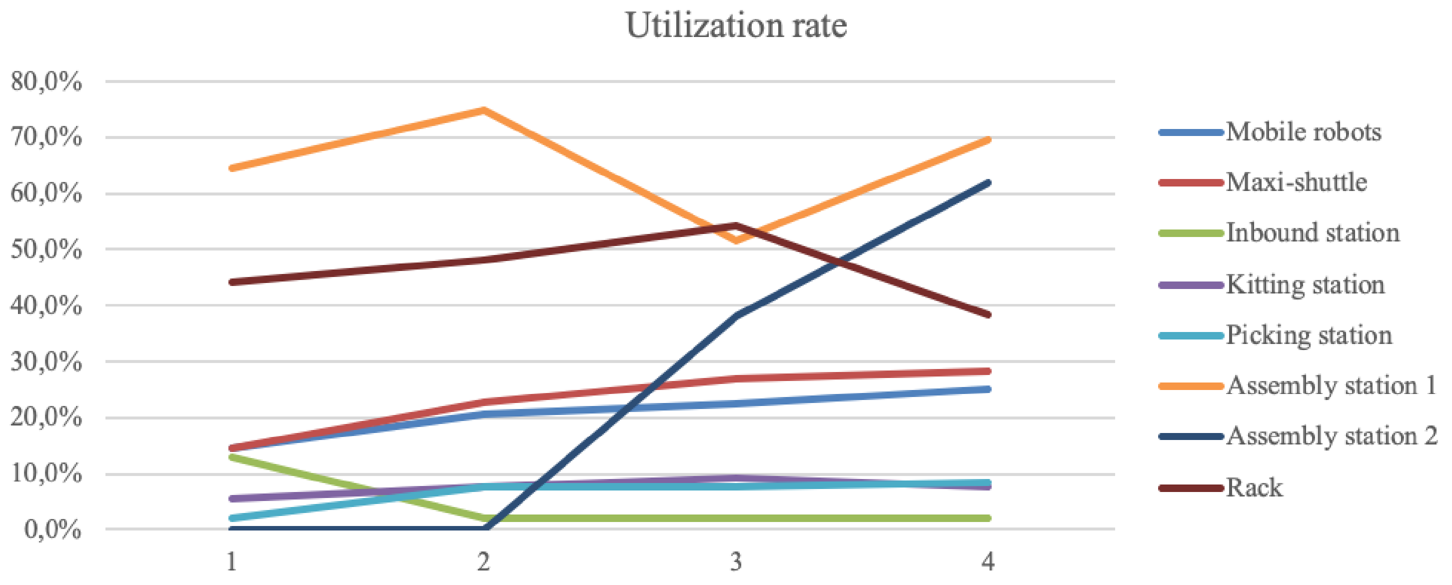



**Figure 10**

Utilization rate

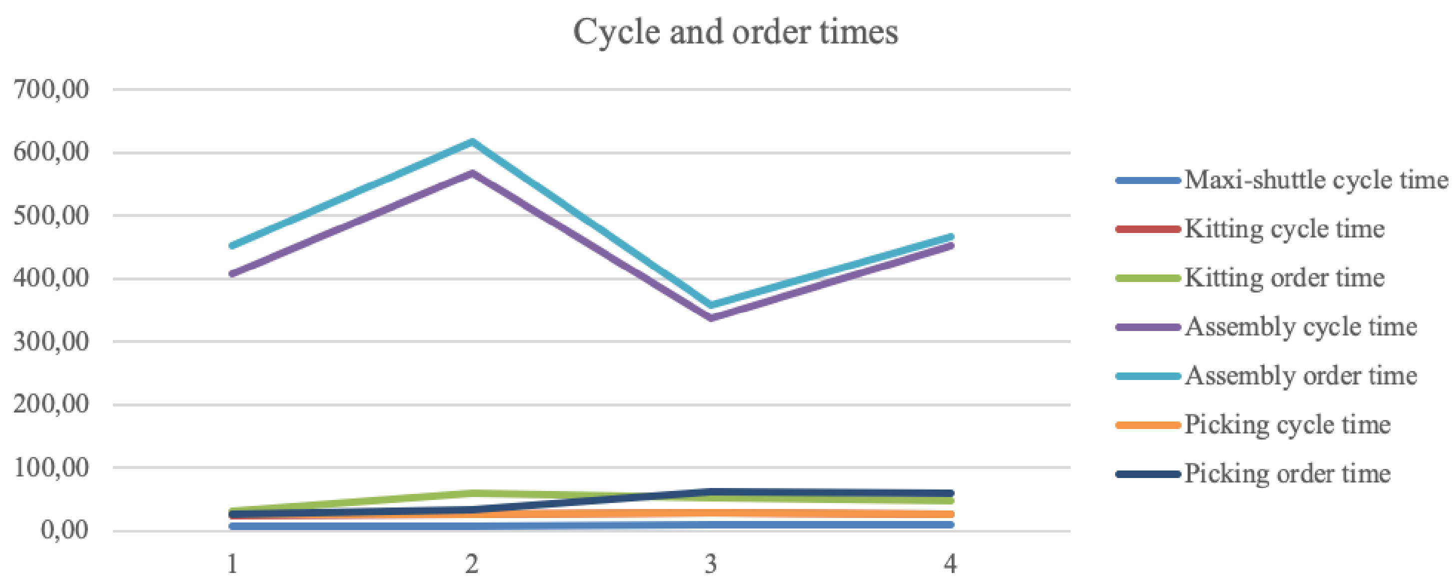



**Figure 11**

Cycle and order times

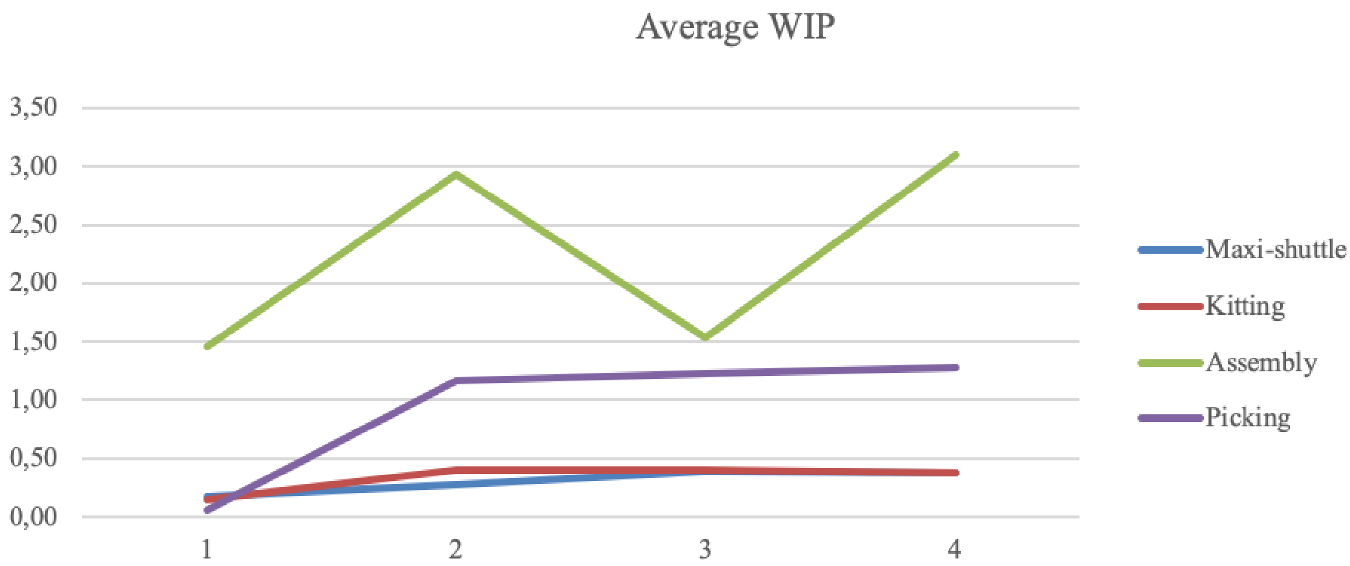



**Figure 12**

Average WIP

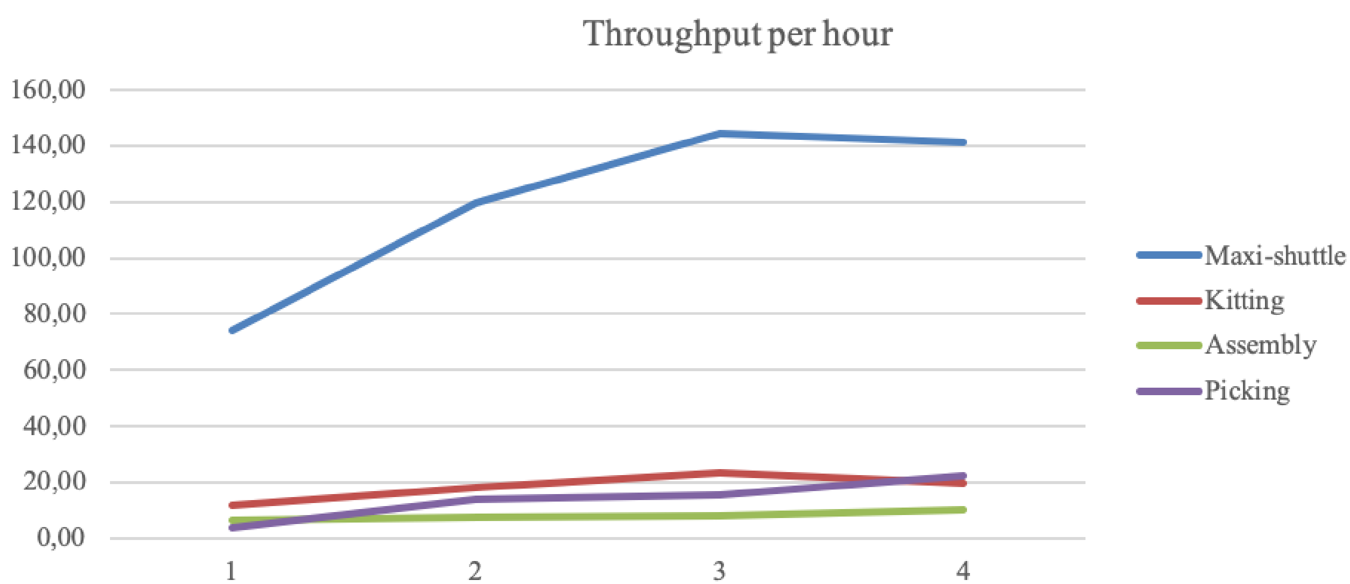



**Figure 13**

Throughput per hour