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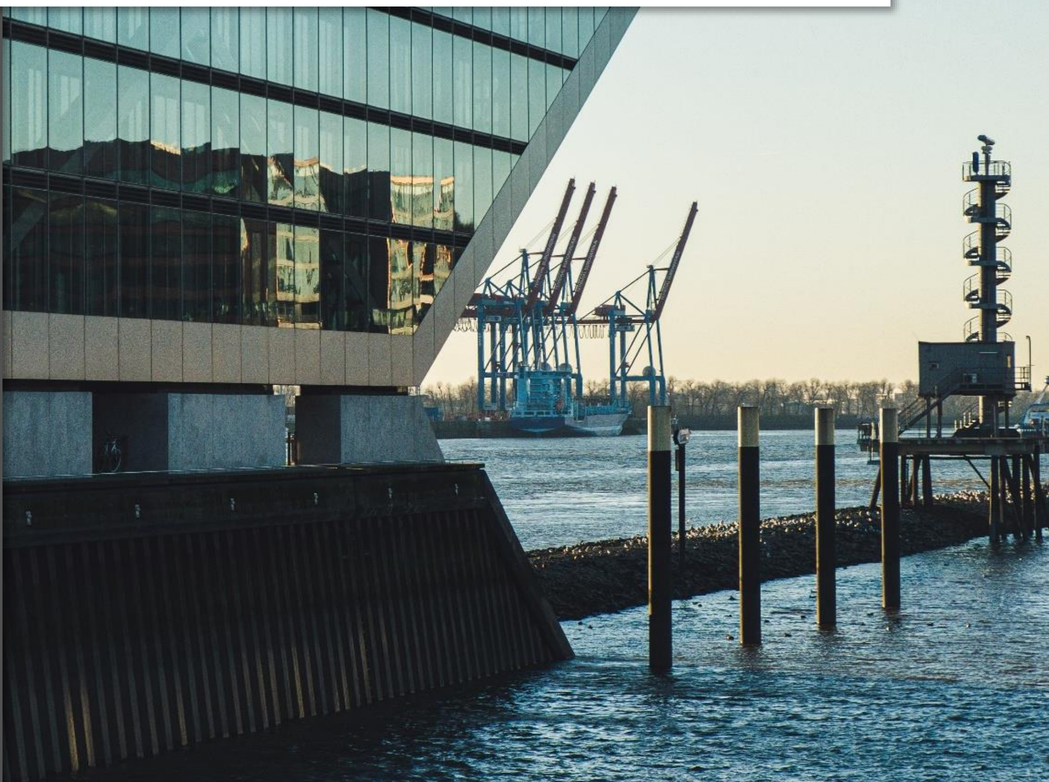

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Scheduling Mobile Robots in Part Feeding Systems

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Purpose: *Industry 4.0 has increased the availability of real-time data in manufacturing systems, but scientific evidence about the value stemming from such data is still lacking in several fields. This paper studies data-driven approaches for the assignment of tasks to a fleet of mobile robots transporting parts to the stations of a mixed model assembly line. The approaches exploit real-time data concerning the robots and assembly stations state.*

Methodology: *An agent-based simulation model of the system, including factory warehouses, assembly stations, and robots, is developed and validated through a real case in the automotive industry.*

Findings: *The paper proposes a model that measures the part feeding system performance in terms of transportation tasks completion time, idle time of the assembly stations due to lack of materials, and amount of inventories at the assembly line. Different data-driven approaches are considered, differing among each other for the type of real-time data used and for the update frequency of the task assignment.*

Originality: *The developed model enriches the ones presented in previous literature by including new information (e.g., robots failures) and new data-driven approaches, such as the dynamic assignment of tasks to robots.*

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1 Introduction

The transition towards Industry 4.0 is deeply changing production and logistics systems, relying on new paradigms such as Internet of Things (IoT) and Cyber Physical Systems (CPS). Factories are turning into networks of smart objects, equipped with sensing technologies and processing units, coupled with communication technologies, with the ability of real-time information perception, transmission, and processing (Qu, et al., 2017). More and more often, such real-time information is being fed to decision support systems, replacing stochastic data and enhancing the responsiveness of decisions. Some application fields have been extensively investigated in the scientific literature, spanning from real-time machine diagnosis for maintenance purposes (O'Donovan, et al. 2015) to production planning and control, driven by real-time information about the status of processes, equipment, and materials, combined with frequently updated customer requirements (Zhang et al. 2017; Müller, et al. 2018). However, the increasing adoption of new technologies makes a large amount of real-time data available also for supporting other decisions, still understudied in the extant literature, for which there is still a lack of scientific evidence about the value stemming from the use of real-time information. It is the case of the task assignment to logistics resources replenishing production stations with materials. In the current business scenario, this problem is becoming more and more complex given the increasing demand volatility and product personalization request coming from the market, which is leading to growing product variety and smaller batch dimensions, often managed with the adoption of mixed-model assembly lines (Faccio, 2014). Factory logistics resources are required to feed assembly stations with small quantities of a wide range of materials, delivered in time for the start of production operations but without piling up too much stock on the shop floor (Schmid and Limère, 2019). The exploitation of real-time data could be an effective way to manage this complexity, by dynamically scheduling logistics resources so as to accommodate the evolving requirements of customers and manufacturing systems, always knowing when, where, and in what way to deliver materials (Hofmann and Rüsch 2017; Tao and Qi, 2019). In literature, most contributions present offline scheduling methods, which generate schedules based on offline data like average part consumptions and layout distances (e.g., Choi and Lee, 2002; Rahman et al., 2020). Only few studies propose online scheduling methods of tugger trains (Zhou and Xu, 2017) and mobile robots (Kousi et al., 2019), exploiting real-time data gathered on the shop floor. However, these studies do not present any tools to estimate the performance improvement resulting from the use of real-time data, compared with offline scheduling.

This paper presents a simulation-based tool for assessing the performance of different scheduling methods of the material handling equipment transporting materials to a mixed model assembly line. Following Kousi, et al. (2019), the problem of assigning replenishment tasks to a fleet of autonomous mobile robots (AMRs) is considered. AMRs are emerging as an alternative to traditional automated guided vehicles (AGVs). AGVs are extensively used in factories also for part feeding at mixed model assembly lines (Boysen, et al. 2015), but require great effort in coordination, lack flexibility, and often ask for human intervention for loading and unloading parts (Kousi, et al. 2019). Compared to AGVs, AMRs do not require expensive investments in navigation infrastructures, since they navigate thanks to simultaneous localization and mapping algorithms (Köseoğlu, Çelik and Pektaş, 2017). Moreover, they are becoming more and more collaborative with loading/unloading capabilities and have better built-in sensing and communication capabilities than AGVs (Liaqat et al. 2019), thus representing a more suitable technology when dealing with the use of real-time data.

The presented simulation tool allows assessing the value stemming from the use of real-time data in the task assignment to a fleet of AMRs, by comparing the performance of offline and online scheduling methods. Real-time data which might be exploited in the scheduling concerns both the AMRs and the assembly stations. The considered performance measures include task completion times, idle times at the production stations due to the lack of materials, and stock levels near the stations.

The remainder of the paper is organized as follows. Section 2 reports a literature review on the use of real-time data in factory logistics and on the scheduling methods of material handling vehicles. Section 3 describes the considered factory logistics system and scheduling methods, while Section 4 presents the simulation model and Section 5 reports its validation through a real case in the automotive industry. Finally, Section 6 includes conclusions and directions for further research.

2 Related literature

This section reports a literature review on the use of real-time data to support decisions in factory logistics systems (Section 2.1) and on the scheduling methods of material handling vehicles adopted in factories and warehouses (Section 2.2).

2.1 Real-time Data in Factory Logistics Systems

The extant literature encompasses a few studies which highlight the aims and potential benefits related to the use of real-time data within decision support systems in factory logistics. Most of these studies adopt qualitative methodologies, based on literature reviews (e.g., Zhang, Zhu and Lv, 2018) and case studies (e.g., Müller, et al. 2018), while only very few contributions present quantitative analyses (e.g., Zhou and Xu, 2017).

Two main purposes of the use of real-time data emerge from the extant literature, namely routing of material handling vehicles (e.g., Zhang, Zhu and Lv, 2018) and task assignment to logistics resources (e.g., Yan, Zhang and Fu, 2019). Different types of real-time data are considered in literature, gathered through different types of connected entities, intended as smart objects equipped with sensing and communication technologies. Three main categories of connected entities are found:

- the moved materials: raw materials, components, work-in-process, and/or finished goods (e.g., Mörth, et al., 2020). The real-time data they gather includes position, quantity, and consumption;
- the material handling equipment (e.g., Thoben, et al., 2017; Zhang, Zhu and Lv, 2018). The gathered real-time data includes the material handling equipment position, battery level, assigned tasks, speed, acceleration, blockages, and operating conditions;
- the destination or consumption points, i.e., warehouses and production stations (e.g., Zhou and Xu, 2017; Kousi, et al., 2019). The gathered real-time data includes inventory levels for each item, queues, cycle times, and stoppages.

The reviewed contributions also list the benefits which could be gained from the use of real-time data. These include: lower inventory levels (e.g., Zhang, et al., 2015), reduced travel time of logistics resources (e.g., Thoben, et al., 2017), reduced assembly errors, and lower idle time of production stations (Kousi, et al., 2019). Nonetheless, the studies either provide only qualitative considerations or present quantitative insights concerning a specific case, without providing a tool to generalize their results. For instance, Thoben, et al. (2017) describe the case of a German gear manufacturer; they show that a dynamic routing of tugger trains, based on real-time vehicles positions and assembly stations states, allows reducing the number of replenishment cycles by more than 60% compared to the use of milk run tours with fixed routes.

2.2 Material Handling Equipment Scheduling

A wide body of literature is available on the scheduling of material handling vehicles in warehouses and factories, which represents one of the main operational decisions in material handling systems and also deeply affects the tactical problem of estimating the required number of vehicles (Le-Anh and de Koster, 2006). The scheduling methods can be grouped into two main classes: offline methods, according to which the scheduling is performed before the start of operations, and online methods, according to which tasks are assigned to material handling vehicles during the running of operations, based on data gathered on the shop floor. Most offline scheduling methods deal with the solution of the vehicle routing problem (VRP), which is a generalization of the traveling salesman problem with more than one agent and with limited capacity of the vehicles to which a series of tasks must be assigned. These problems are known to be NP-hard and literature presents a number of heuristics to cope with them (e.g., Laporte, 1992), using deterministic and static information known in advance. The developed schedule is very sensitive to changes in information (Mes, et al. 2007). In addition, the time required for the algorithms to update the schedule may not allow a timely response to unexpected events such as equipment failure or rush orders; therefore, it is not practically feasible to use offline methods in dynamic and stochastic environments (Le-Anh & De Koster, 2006; Li, et al., 2019). Online scheduling methods allow assigning tasks to vehicles based on real-time or nearly real-time information gathered on the shop floor (Li, et al., 2015). Egbelu and Tanchoco (1984) study alternative methods, where the load is assigned to a vehicle based on the optimization of one parameter which might be either the distance between the vehicle and the load, the vehicle idle time, or the vehicle mean utilization.

More recent studies present methods based on the combination of different parameters. For instance, Li, et al. (2019) present a mixed-integer programming model for AGVs scheduling in warehouse sorting operations, where the objective function to be minimized includes a weighted average of the makespan, the number of AGVs in the system, and the amount of electricity used by the AGVs. Shifting the focus to mobile robots, Nielsen, et al. (2017) consider a system where a single robot transports small unit loads from a supermarket to multiple-step feeders of a machine. When the stock level at a feeder reaches a threshold value, a material replenishment request is issued. A genetic algorithm is proposed for the scheduling problem, aiming at minimizing the total robot travel time and the total tardiness of the tasks. Kousi, et al. (2019) consider a fleet of AMRs feeding a mixed-model assembly line and present a service-oriented architecture that orchestrates the material replenishments at assembly stations and collects real-time data from the shop floor. Replenishment requests are issued based on real-time inventory levels, and the scheduling method assigns tasks to the AMRs so as to minimize the weighted average of the overall traveled distance and the tour duration, which are computed using the real-time position of robots and considering a fixed battery charging time for each robot.

3 System Description

This section describes the general layout of the system considered in this study (Section 3.1) and the scheduling process of mobile robots within this system (Section 3.2).

3.1 Main Components and Layout

The investigated system consists of a mixed-model assembly line and a number of supermarkets. The line, made of several assembly stations, can produce different types of finished products, using different types of materials. Each finished product type requires using a known quantity of one or more material types at each station and entails a certain service time. In every production shift, a target production should be achieved within the available time. Materials are handled in small boxes, containing multiple units of one material type each. At each assembly station, at least one box of every material type used at that station is stored. Moreover, extra stock of each material type is kept at the supermarkets, which are decentralized warehouses located on the shop floor. AMRs are in charge of replenishing assembly stations with materials. Each robot can move up to multiple boxes simultaneously, and a typical robot movement involves the arrival at the supermarket, the load of one or more boxes, the travel to the stations requiring the boxes, and the unloading of the boxes. Robots might incur in failures (e.g., stoppages due to the presence of obstacles that cannot be avoided or mechanical failures) and have a certain level of battery autonomy, which is restored every time the robot is sent to a charging station. For the sake of example, a system with 4 assembly stations, 2 supermarkets, 6 types of materials, 2 robots, and 1 charging station is shown in Figure 1.

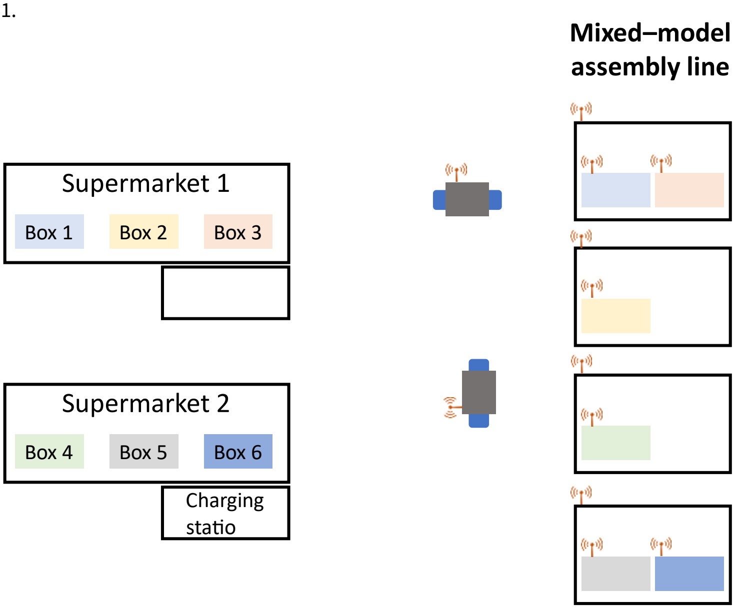

Figure 1: System layout – Example

Each supermarket or station can process one robot at a time. Therefore, robot queues in front of supermarkets and stations are taken into account.

The system also includes a central supervisor node assigning replenishment tasks to AMRs. Depending on the system configuration, the supervisor can also receive real-time data from robots (i.e., position, state, and battery level) and assembly stations (i.e., state and inventory levels inside each box stored at the station), and exploit such data in the scheduling process.

3.2 Scheduling Process

The central supervisor may assign tasks to AMRs according to three different scheduling methods, differing among each other for the task assignment logic, for the use of real-time data, and for the schedule update frequency based on such data. The simplest one, called Offline-First Available (OFF-FA) method, is an offline scheduling method that assigns replenishment tasks to the first available robot, without exploiting real-time data from the system. If all robots are busy, the task is assigned to the robot with the minimum number of already assigned tasks. The replenishment requests are generated according to a periodic review model and events such as station stoppages or robot failures are not taken into account.

The remaining three methods work according to the two-phase task assignment process described in the following. Whenever the inventory level of a material at an assembly station reaches a pre-defined threshold level, a replenishment request for a box of that material is issued and the task allocation procedure is initiated. The replenishment request is split into a pick-up and a drop-off task, executed by the same robot. Since each robot can be in charge of more than one replenishment request at a given time, a multi-load task assignment method is implemented. The aim is to assign tasks to robots in order to minimize the total execution time of the schedule and avoid idle times of the assembly stations due to lack of materials. More in detail, the scheduling process can be divided into two main phases (Figure 2).

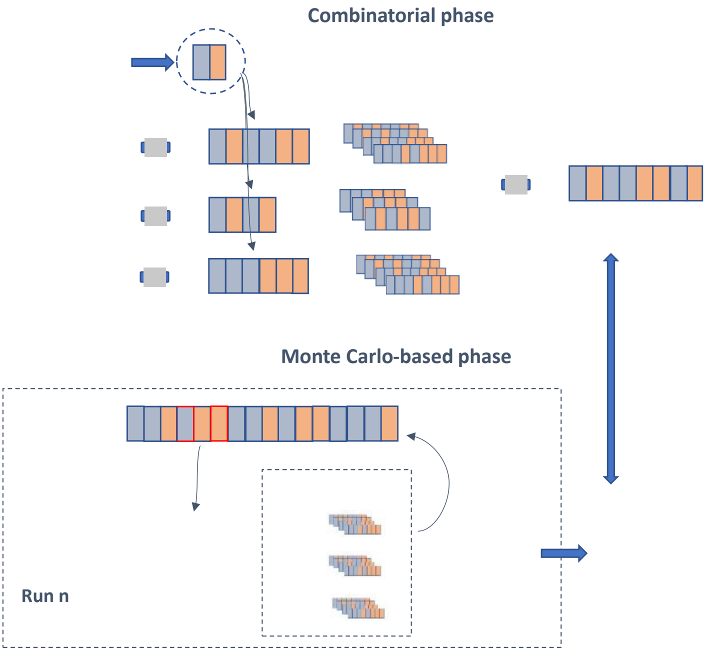

Figure 2: Scheduling process

In the Combinatorial phase, whenever new pick-up and drop-off tasks must be assigned, the method compares all possible tasks permutations for each robot. Permutations represent sequences of tasks created starting from the current schedule of each robot and adding the new tasks. Only feasible permutations are considered, i.e., sequences where pick-up locations (i.e., supermarkets) are visited before the corresponding drop-off locations (i.e., assembly stations). Moreover, permutations which imply the loading of more boxes than the actual capacity of the robot are excluded. The permutations are compared based on the total schedule time, an indicator corresponding to the time needed to complete the entire sequence of tasks, increased by a penalty every time a station is expected to be idle due to lack of materials. To compute such an indicator, the finishing time of each replenishment request must be estimated and compared with the estimated time at which the station reaches the idle time. Thanks to the possibility to exploit real-time data, in online scheduling methods the finishing times of the requests are estimated based on the actual robots positions and states. Moreover, the time of station blockage is estimated starting from the actual inventory level. Besides pick-up and drop-off tasks, also battery charging times are included when computing the total schedule time. An opportunity charging strategy is adopted (Le-Anh & De Koster, 2006): a robot is charged either when it is idle and its battery level is below a certain threshold (e.g., 60%), or when it reaches a critical battery level (e.g., 20%). In the online methods, the time of charging end can be estimated with the real-time battery level and queues at the charging station, thus allowing to assign tasks to the robots while they are charging. At the end of the Combinatorial step, the permutation leading to the lowest total schedule time is identified and the task is assigned to the corresponding robot. In the ensuing Monte Carlo-based phase, reallocations of tasks among different AMRs are evaluated. In fact, given the stochasticity of events (e.g., robot failures and machine stoppages), a task previously assigned to a robot could provide a lower total schedule time if assigned to another robot. Therefore, a Monte Carlo simulation-based procedure consisting of multiple runs is followed. In each run, a couple of pick-up and drop-off tasks are randomly picked from the pool of all the tasks which have not started yet, and all possible task permutations are evaluated, considering all the AMRs. If this phase provides a better schedule than the previous one, tasks are re-allocated according to it.

The three scheduling methods are called Offline-Two-Phase assignment (OFF-TP), Real-time-Two-Phase assignment (RT-TP), and Real-time-Two-Phase Dynamic assignment (RT-TPD). The OFF-TP is an offline method that feeds the developed two-phase task allocation process with average and static data, like the average travel distances between each couple of elements in the system and the average consumption of each material. Although being an offline scheduling method, the OFF-TP differs from the simpler OFF-FA because it uses a higher amount of data and aims to minimize the total schedule time. The RT-TP is an online scheduling method according to which a new replenishment request for a box at a station is triggered when the actual level of inventory reaches the threshold value set for the corresponding material type. Schedule times are computed based on actual AMRs positions and battery autonomy, AMRs and stations states, and actual queues. Finally, the RT-TPD is an online method that differs from the RT-TP for the schedule update frequency: the schedule is updated dynamically, based on real-time information continuously gathered on the shop floor. In other words, the two-phase task assignment process is run not only when a new replenishment request is issued, but also at defined time intervals; the shorter the time interval, the more the schedule is reactive to stochastic events.

4 Model Description

This section presents the agent-based simulation model developed to estimate the performance resulting from the use of the task assignment methods described in Section 3.2. Agent-based simulation has been deemed suitable due to the nature of the investigated system, where AMRs, supermarkets, stations, and the central supervisor interact with each other, driving operations planning and execution. In fact, differently from other simulation approaches used in this field such as discrete-event (Yin and Mckay, 2018), agent-based simulation allows representing complex interactions among the actors of a system, accounting for state variables that interrelate with one another and change on a continuous basis (Bonabeau, 2002).

The pivotal elements of an agent-based simulation model are the so-called agents, which attempt to maximize their utility functions by interacting with other agents and resources. Each agent is described by a series of attributes defining its state, which evolves in time as a reaction to external events. In the developed model, the agents are the AMRs, the assembly stations, the supermarkets, the charging stations, and the central supervisor. The other elements in the environment, namely boxes, tasks, and WIPs (i.e., products being assembled at the stations), are represented by data structures, rather than agents, since their relationship with the other entities is simpler and does not require evolution of states.

The model has been developed in Python language, using the Mesa module. In this module, a method called STEP is run at every simulation cycle for each agent and enables the progression of states of the agents. Three types of classes are defined in the developed model. The Model class ensures that each other agent in the model progresses its state at every simulation cycle, by calling the STEP method for every agent. The Model class also populates the model with instances and supervises the production orders, thus stopping the simulation if the target production has been achieved or the defined maximum number of cycles (i.e., the available time for production) has been reached. The Space components class describes the space the agents operate in. Finally, the Agent classes describe the model agents. The following subsections (4.1 to 4.5) briefly describe the Agent classes defined in the developed model. Then, Section 4.6 explains how the model measures system performance.

4.1 Autonomous Mobile Robot Class

The AMR agent is in charge of transporting materials according to the tasks assigned to it by the supervisor. Three types of states are allowed for an AMR agent:

- Committed states: the AMR is either Charging or fulfilling replenishment tasks (i.e., Moving, Waiting to load, or Waiting to unload).
- Idle state: no tasks are assigned to the AMR. As soon as the supervisor assigns one or more tasks to the AMR, the agent transitions to a Moving state. Otherwise, if no tasks are assigned for a certain amount of time and the battery level is below a threshold, the AMR is sent to a charging station, thus transitioning to a Charging state.
- Error: the robot is in failure mode. After a certain time to repair, the AMR exits this state and enters the Idle state.

4.2 Assembly Station Class

Each assembly station agent represents one of the stations of the mixed-model line. Like the AMR agent, the assembly station can be described as a sequence of states reached upon fulfillment of certain conditions. Given the complexity and the number of activities it carries out, this agent is divided into three main parts (production, inventory, robot queue), described by a state each.

4.2.1 Production

Every station has a list of production orders that it must fulfill before the end of the available time. The possible states are:

- Production state: the station is processing a product.
- Waiting for production state: the station is tasked with a production order, but the required material is not fully available. As soon as the material is replenished, the agent transitions to the Production state.
- Idle state: the station is not processing any product. This is the starting state, which is also temporarily entered every time the station needs to transition from the Production state to the following state (Production or Waiting for production).

4.2.2 Inventory

Inventories consist of boxes with materials stored at the station. Each material inventory has its own state:

- Wait for robot state: inventory levels are checked every time the station finishes assembling one product. The agent enters this state when the inventory level is equal to or below the threshold triggering a replenishment request or below the quantity needed to process the following product. The state is exited as soon as the material is replenished.
- Full state: inventory is above the threshold level and is enough to fulfill the following production order.

4.2.3 Robot Queue

This part of the assembly station agent represents the queue of AMRs waiting to unload the boxes they are carrying. The possible states are:

- Idle state: no robots are unloading boxes and the robot queue is empty.
- Unloading boxes state: one or more robots are waiting to unload boxes. Every time an AMR approaches the assembly station, a function is called to evaluate the AMR state. If the AMR state is Waiting to unload (Section 4.1), the robot queue state transitions to Unloading boxes. Then, once the unloading time has passed, the station either waits for the next robot in the queue to unload or transitions to the Idle state if the queue becomes empty.

4.3 Supermarket Class

Supermarket agents are modeled as a simpler version of the assembly station agents, without the production and the inventory parts. Therefore, both the possible states (called Idle state and Loading boxes state) and the conditions for the transition from one state to another are analogous to the ones described in Section 4.2.3. The only difference is that the states are related to the loading, rather than the unloading, of boxes by the AMRs.

4.4 Charging Station Class

The charging station agents are modeled similarly to the supermarkets. Their possible states are:

- Idle state: no AMRs are currently charging and the robot queue in front of the charging station is empty.
- Charging state: the station is charging a robot. The agent enters this state when an AMR, whose state is Charging, approaches the charging station. Then, once the charging time has passed, the agent either remains in the Charging state, if there is at least one more robot in the queue waiting to be charged, or transitions to the Idle state.

4.5 Supervisor Class

The supervisor agent represents the central node that receives replenishment requests from assembly stations, identifies the target supermarket where the required materials are stored, translates replenishment requests into tasks, and assigns tasks to the fleet of AMRs. In case an online scheduling method is used, the supervisor also continuously monitors the states of all the other agents in the system, as well as the real-time positions and current task lists assigned to each robot and the queue lengths at all stations and supermarkets. Then, it uses such real-time information for the task assignment. The procedure and methods followed by the supervisor agent to assign tasks to AMRs are described in Section 3.2.

4.6 Performance Measures

The developed model allows assessing three system performance measures. First, the average completion time, measured as the average time needed by an AMR to fulfill a replenishment request, from the pick-up of the box at the supermarket to its drop-off at the target station. It includes movement, queuing, and loading/unloading times. The lower this measure, the better the ability of the AMR fleet to promptly react to replenishment requests. Second, the idle time, measured as the percentage of the available time in which stations are not producing due to unavailability of materials. The idle time, resulting from the material handling system performance, directly affects the efficiency of assembly operations and should be eliminated or kept to a minimum. Finally, the average stock level of each material at the assembly stations. An effective scheduling method should allow reducing this indicator, consequently decreasing the amount of floor space on the shop floor dedicated to storage purposes, hence maintaining a high efficiency of assembly operations.

5 Model Validation

This section describes the validation of the developed agent-based simulation model. The model is validated through its application to a real industrial case concerning a car assembly plant where a fleet of 11 AMRs replenish assembly stations with kits. For this purpose, both the considered layout and the model parameters are adapted to the case. The layout consists of: a U-shaped assembly line, supermarkets located all around the line, and one AMR charging station placed next to each supermarket. The line is made of 23 stations and its takt time is 36 minutes. Supermarkets are organized so that the materials needed at an assembly station are stored in the closest supermarket. The distance between a supermarket and the closest station is 9 meters, while the distance between two neighboring stations is 8.5 meters. Kits, i.e., small trolleys containing the parts needed to assemble one product, are prepared at the supermarkets. The assembly of each product requires two different kits at each station. Two kits of each type are stored at a station and every time one of the kits is emptied, a replenishment request is issued. Then, replenishment tasks are allocated to AMRs based on the OFF-FA scheduling method (Section 3.2). After the task assignment, the AMR reaches the supermarket input point, autonomously loads the kit, transports it to the station, unloads the kit, loads an empty trolley, and transports it back to the closest supermarket. An average speed of 0.9 meters/second and fixed loading/unloading times of 30 seconds are considered for the AMRs. Moreover, every 36 minutes, each robot goes to the closest free charging station, where it remains until its battery level is restored to full.

In order to validate the model, its outputs are compared with the real values measured in the industrial case. The outputs are the average task completion time, the average distance traveled by AMRs to fulfill a replenishment request, and the average robot utilization (i.e., percentage of the available time in which a robot is performing replenishment tasks). As shown in Table 1, the model provides a satisfactory estimation of the real values, which are only slightly underestimated. The percentage difference is around 3% for the average task completion time and robots utilization, while it increases to 4.7% for the average distance traveled by robots. This last value is explained by the deviations between the simulated paths, assumed to be straight, and the real ones, which are affected by obstacles that the AMRs might need to avoid.

Table 1: Validation results

Output	Real case	Simulation	% difference (Simulation vs. Real case)
Avg task completion time [min]	7.41	7.2	– 2.8%
Avg distance travelled [m/task]	270.9	258.1	– 4.7%
Avg AMR utilization	86.1%	83.6%	– 3.0%

6 Conclusions

The growing adoption of data sensing, transmission, and processing technologies is increasing the amount of real-time information available to support decisions within modern factories. Considering mobile robots feeding parts to assembly lines, this paper provides, for the first time in literature, a model for estimating the performance improvements resulting from the use of real-time data in the scheduling of material handling activities. The developed model also accounts for new type of data, never considered in previous studies (e.g., robot failures), and new data-driven approaches, such as the dynamic assignment of tasks to robots.

From an academic viewpoint, this study stimulates further research on the value stemming from the real-time data availability offered by the Industry 4.0 paradigm. From a practitioner viewpoint, the developed model can be applied in industrial contexts to support both the comparison of alternative scheduling methods and the sizing of the mobile robots fleet.

Some limitations should be acknowledged, mainly related to the model assumptions. In particular, the model considers only one type of production system (i.e., mixed-model assembly line) and a specific layout of the factory logistics system, consisting of a set of supermarkets from which all material replenishments originate. Future studies could adjust the model to take into account also different kinds of systems, like job shops, and alternative layouts. For instance, they could consider a setting in which direct replenishments of materials from the central factory warehouse are possible. Future research should also focus on applications of the developed model, so as to compare the proposed scheduling methods and develop insights on the value stemming from the use of real-time data. Moreover, economic analyses could be performed, thus comparing the methods in terms of overall investments in the robot fleet and in data gathering, transmission, and processing technologies. Finally, sensitivity analyses could be carried out to investigate how performance is affected by critical parameters and choices like the demand level, the inventory reorder policies, and the robots capacity.

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