



Invited Review

Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda



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ABSTRACT

Autonomous mobile robots (AMR) are currently being introduced in many intralogistics operations, like manufacturing, warehousing, cross-docks, terminals, and hospitals. Their advanced hardware and control software allow autonomous operations in dynamic environments. Compared to an automated guided vehicle (AGV) system in which a central unit takes control of scheduling, routing, and dispatching decisions for all AGVs, AMRs can communicate and negotiate independently with other resources like machines and systems and thus decentralize the decision-making process. Decentralized decision-making allows the system to react dynamically to changes in the system state and environment. These developments have influenced the traditional methods and decision-making processes for planning and control. This study identifies and classifies research related to the planning and control of AMRs in intralogistics. We provide an extended literature review that highlights how AMR technological advances affect planning and control decisions. We contribute to the literature by introducing an AMR planning and control framework to guide managers in the decision-making process, thereby supporting them to achieve optimal performance. Finally, we propose an agenda for future research within this field.

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1. Introduction

In recent decades, the technology in materials handling has advanced rapidly. One major development is the evolution of automated guided vehicles (AGV) into autonomous mobile robots (AMR). Since 1955, when the first AGV was introduced (Muller, 1983), the guiding system that forms the core part of AGV material handling systems has evolved along various stages of mechanical, optical, inductive, inertial, and laser guidance into today's vision-based system (Fig. 1). This vision-based system uses ubiquitous sensors, powerful on-board computers, artificial intelligence (AI) and simultaneous location and mapping (SLAM) technology, enabling the device to understand its operating environment and to navigate in facilities without the need to define and implement reference points in advance. This has opened a new dimension in navigational flexibility.

Conventional AGVs can only follow fixed paths and move to predefined points on the guide path (Fig. 1(a)–(f)). By contrast, AMRs can move to any accessible and collision-free point within

a given area (Fig. 1(g)). Small changes due to, for example, a machine layout change would typically take substantial time for most AGV guidance systems, cause periods of inactivity, and risk economic losses and decreases in productivity. AMRs, however, can adapt quickly to changes in the operating environment.

The need for more flexibility has driven the development of AMRs, not only in navigational ability but also in the services they can provide. Compared to AGVs, which have been characterized as computer-controlled, wheel-based load carriers for horizontal transportation without the need for an onboard operator or driver (Le-Anh & De Koster, 2006) to be used for repeated transport patterns, AMRs can provide many services beyond mere transport and material handling operations, such as patrolling and collaborating with operators. Combined with the ability to take autonomous decisions, these mobile platforms can offer flexible solutions. The autonomy of AMR vehicles implies continuous decision-making about how to behave in an operating environment consistent with prevailing rules and constraints. A substantial challenge lies in the complete absence of a human supervisor who knows the system's limits. An AMR must, therefore, monitor its own state autonomously, spot potential system faults and react appropriately.

The AMR's hardware and control software facilitate advanced capabilities for autonomous operation, not only for navigation and

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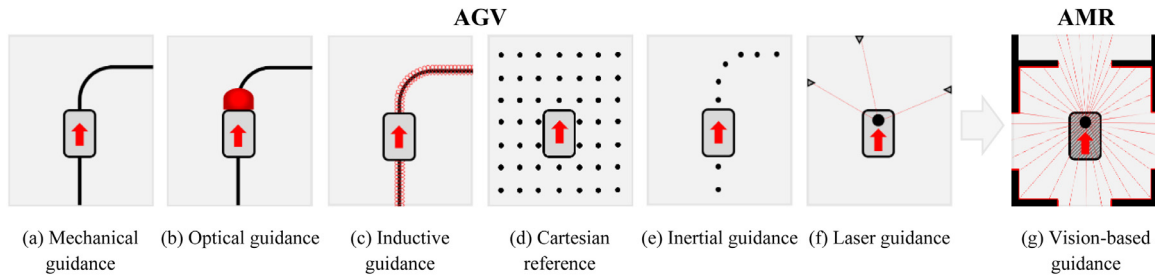


Fig. 1. Guiding systems for AGVs and AMRs (top view of the system).

object recognition but also for object manipulation in unstructured and dynamic environments (Hernández et al., 2018). These developments have led to the decentralization of decision-making processes. Compared to an AGV system in which a central unit takes control decisions such as routing and dispatching for all AGVs, AMRs can communicate and negotiate independently with other resources like machines and systems such as enterprise resource planning or material handling assessment and control software (Fig. 2), and take decision themselves. This reduces the need for centralized, external control (Furmans & Gue, 2018). The goal of the AMR decentralized decision-making is to react dynamically to demand or changes and allow each vehicle to continuously optimize itself.

The AMR concept is not new. The first generic AMR patent was issued in 1987 (Mataboni, 1987). Since then, it has been discussed mainly in the fields of robotics and information technology, but it has recently emerged in logistics applications and its importance is expected to increase significantly in the near future. In fact, it has been estimated that more than 13,000 AGV and AMR systems have been installed globally (Bechtsis et al., 2017). Currently, hundreds of suppliers worldwide supply autonomous robots. Through the use of generic components, e.g. sensors, driving and steering systems, batteries, manipulating equipment and processing devices, basic vehicles can be assembled at a fairly low cost. Traditionally, the main sectors with AGV applications were manufacturing systems, warehouses and container terminals (Le-Anh et al., 2006),

but their areas of application and the services they can provide have increased significantly. AMRs can now be found in industrial, healthcare, hotel, security and domestic settings, performing a wide range of tasks.

Besides machine loading and transportation tasks, AMRs can be used as assistive systems as they can interact with humans as coworkers (Fig. 3(c)). In automotive car assembly, AMRs with manipulators can assist workers and together mount heavy parts of a car body at different stages along the assembly line (Angerer et al., 2012), thus increasing both productivity and quality while simultaneously reducing fatigue levels among workers.

In warehouses, AMRs collaborate with operators in order picking (Fig. 3(p)). AMRs carry a few small containers inside the picking areas and stop in front of the location where the operator must pick the next item. They then move to the next location independently. When all items in a given order have been collected, the AMR autonomously travels to the packing and consolidation area, where it is emptied and reassigned to a new set of orders (Meller et al., 2018; Azadeh et al., 2019a). This technique enables a zone-picking strategy that optimizes operator and AMR picking and traveling efficiency.

The strength of AMRs is especially well demonstrated in narrow-aisle, high-traffic environments like those found in warehouses and hospitals. AGVs do not enter wards or departments for safety and delivery performance reasons; instead, they deliver goods close to the entrance. AMRs, by contrast, have greater access

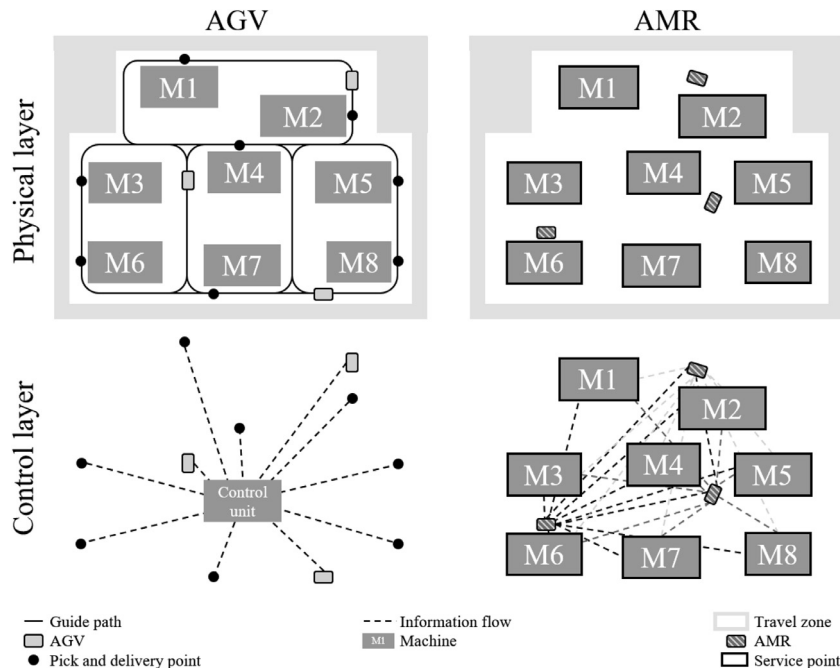


Fig. 2. Centralized AGV control and decentralized AMR control.

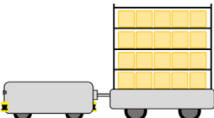


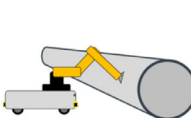


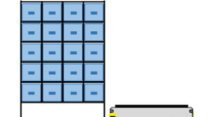
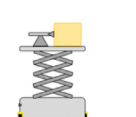

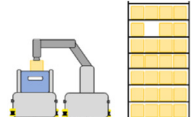


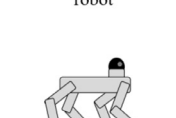
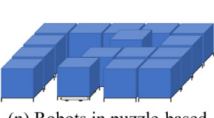
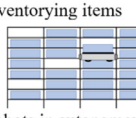



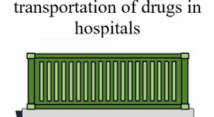



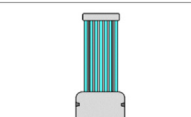
	Material handling	Collaborative and interactive	Full service
Manufacturing	 <p>(a) Anchor / Tow / Train</p>  <p>(b) Robot with shelf unit</p>  <p>(c) Collaborative robot</p>  <p>(d) Robot arm with sanding equipment for windmill blades</p>  <p>(e) Robot with lifting equipment</p>  <p>(f) Robot with conveyor top</p>		
Warehousing	 <p>(g) Order fulfillment robot in robotic mobile fulfilment systems</p>  <p>(h) Picking robot</p>  <p>(i) Collaborative fetching robot</p>  <p>(j) Picking robot and fetching robot</p>  <p>(k) Sorting robot</p>  <p>(l) Robot for localizing and inventorying items</p>  <p>(m) Surveillance robot</p>  <p>(n) Robots in puzzle-based storage systems</p>  <p>(o) Robots in autonomous vehicle storage and retrieval systems</p>  <p>(p) Collaborative order picking robots</p>		
Other intralogistics environments	 <p>(q) Robot for secured transportation of drugs in hospitals</p>  <p>(r) Luggage carrier robot in hotels</p>  <p>(u) Robot in container terminals</p>  <p>(v) Car valet robot at car parks</p>	 <p>(s) Robot for patient guidance in hospitals</p>  <p>(x) Robot with telepresence device in hospitals</p>	 <p>(t) Robot for disinfection of hospitals</p>

Fig. 3. Types of AMRs and examples of applications.

to nearly all departments and can be used for critical and just-in-time deliveries like cancer medicines or radioactive therapeutic and diagnostic medicines of which the correct dose decays rapidly (Fig. 3(q)). In addition to transport tasks, they can provide services, such as disinfecting rooms, telemedicine or guidance assistance (Fig. 3(s, t, x)) (Fragapane et al., 2020a). AMRs can effectively reduce manual material handling in hospitals, providing more time for patient-related activities and increasing value-added time for direct-care staff.

The activities performed characterize and divide AMRs into three main groups. They provide (I) material handling (retrieve, move, transport, sort, etc.), (II) collaborative and interactive activities and (III) full-service activities (Fig. 3). They come with the following attributes (Hernández et al., 2018; Indri et al., 2019):

- Decentralized control: applying methodologies and technologies of intelligent, cognitive and behavior-based control to maximize flexibility and productivity performance.

- Platform operation: providing a platform to extend an AMR's capabilities and application possibilities beyond common material handling activities.
- Collaborative operation: working together with humans or other AMRs in a swarm.
- Ease of integration: integrating fast and cost-efficient AMRs into a factory or other facility.
- Scalability: increasing or decreasing the number of AMRs without being hindered by structural change.
- Robustness: providing resilience, i.e. systems that can recover after failure.

To summarize, the authors propose and use the following definition in this study:

Autonomous mobile robots are industrial robots that use a decentralized decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area.

The increasing ability of AMRs to take over tasks and activities and the fact that AMRs navigate, operate and interact with humans and machines differently than AGVs requires a new decision structure. Managers need guidance during decision making in order to achieve optimal performance. For instance, at the strategic decision level, it is essential to define the degree of control decentralization of assistive material handling activities for AMRs in car manufacturing. At the tactical level in warehouses, work zones must be determined for collaborative AMRs. At the operational level in hospitals, safe and low contagion-risk AMR travel paths must be planned.

The literature on AMRs is fragmented and has a largely technological focus. The lack of a unified, accepted definition among practitioners and researchers has also hampered research in this field. AGVs have dominated the literature on vehicle planning and control systems. Vis (2006) and Le-Anh et al. (2006) distinguish key decision areas, such as guide path design and determining the number and locations of pick-up and delivery points, while Bechtsis et al. (2017) provide a literature review focusing on sustainability aspects in AGV planning and control. The greater degree of autonomy, applicability, and flexibility provided by AMRs result in a large number of different decisions on strategic, tactical and operational level that must be taken, and this number continues to grow. However, since their applications are not yet abundant, AMRs have not been investigated sufficiently from an academic perspective. The current methods of AGV planning and control remain to be analyzed, and it is worthwhile to assess whether they can be transferred, extended, or modified for AMRs.

Starting with the literature on AGVs, the present study identifies and classifies research related to the planning and control of AMRs and proposes an agenda for future research in this field. The focus is on the main elements of autonomy (i.e. decision-making), mobility (i.e. free navigation) and robotics (i.e. providing services). We examine the following research questions:

- How do the technological advances of AMRs affect planning and control decisions?
- What are the dominant approaches and methods in the literature on AMR planning and control?
- What future research is needed in AMR planning and control?

To answer these questions, we carried out a literature study that inventoried articles in refereed journals; English-language sources from online databases like ScienceDirect, Web of Science and Google Scholar were included. The following keywords (and their variants) were used: 'Automated Guided Vehicle', 'Autonomous Intelligent Vehicle', 'Autonomous Mobile Robot', 'Mobile Robotic Fulfilment', 'Collaborative Mobile Robot', 'Mobile Service Robot' and 'Puzzle Based Storage System'. We then narrowed down our search. First, we focused only on articles published in the last 15 years. Older material on AGVs has been adequately covered in two literature reviews by Le-Anh et al. (2006) and Vis (2006), which describe the main methods and approaches before 2006. Second, we excluded conference proceedings, professional journals, book chapters and doctoral dissertations, since we assume that important research has eventually appeared in refereed academic journals. Third, we focused on high-impact journals and included only articles published in journals with a Scimago Journal Rank higher than 0.5. Next, we manually screened the titles and abstracts of all 302 remaining articles. Only papers with full texts in English and related to either AMRs or AGVs (if relevant and applicable for AMRs) were included. In the final step, all the remaining articles were full-text screened to confirm their relevance to the planning and control of AMRs. Examining the reference lists, some highly relevant articles, cited multiple times but not identified previously, have also been added. A total of 108 articles were included in the final review.

The rest of the paper is organized as follows. Section 2 presents the crucial technological advances of AMRs and explains how they have affected the AGV decision areas and decisions. In Section 3, we introduce a decision-making framework for AMRs indicating the main changes compared to AGV decisions. Section 4 describes the planning and control decisions and the operational research methods applied. In Section 5, we quantify and summarize the current approaches to identify the gaps in literature, and present detailed recommendations for future research areas. We conclude in Section 6.

2. Technological advances impacting AMRs

The evolution of AGVs into AMRs has become possible due to new hardware (Section 2.1) and software (Section 2.2) technologies.

2.1. Hardware

2.1.1. Sensors

AMRs are typically equipped with a wide array of small, low-cost, and power-efficient sensing technologies providing input data for autonomous navigation. Integrated laser scanners such as Light Detection and Ranging (LiDAR), 3D cameras, accelerometers, gyroscopes, and wheel encoders, which provide information on wheel positions to calculate the distance that the robot has driven or turned, and capture and transmit enormous amounts of data about the AMR's immediate, extended and anticipated environments, along with its internal condition (De Silva et al., 2018). While LiDAR laser scanners provide a very precise distance point cloud relative to the AMR in its environment, 3D cameras provide wide-angle support that enables the visual recognition of obstacles. These technologies have become popular due to their easy dynamic usage and speedy rendering of results. Compared to AGVs, AMRs are not 'blind', but have full recognition of the environment. This affects decisions about guide path choice, collision and deadlock prediction and avoidance, and failure management. Sensing the environment allows an AMR to assist, collaborate and interact with humans and machines, which means more decisions to make.

2.1.2. Robot locomotion mechanism

The locomotion mechanism of a robot has a strong impact on its stability, manoeuvrability, and kinematics. Most AGVs have either one steerable traction wheel in the front with supporting wheels in the back or two independently driven wheels with several, omnidirectional supporting wheels, thus providing a cost-efficient and low complexity trade-off against the above-mentioned factors. Different combinations, configurations, and arrangements of AMR wheels or legs exist. A high level of manoeuvrability can be achieved by powering Swedish or spherical wheels or increasing the number of legs, thus allowing the robot to move at any time in any direction along the ground plane regardless of the orientation of the robot (Siegwart et al., 2011). Since many intralogistics activities require a high level of stability, wheeled AMRs are typically the first choice. However, movement in rough terrain is typically attempted with legged AMRs. Several companies have presented legged AMRs for activities in intralogistics; examples include SPOT by Boston Dynamics (<https://www.bostondynamics.com/>) and ANYmal C by ANYbotics (<https://www.anybotics.com/>). The increased flexibility in the movement and positioning of AMRs requires appropriate path planning methods, and the service points should be correctly determined.

2.1.3. Batteries

Higher energy capacity and improvements in charging methods, ranging from conventional plug-in connector power supplies

to wireless power transfer, have a significant impact on the battery management of AMRs. Studies indicate that wireless power transfer can be applied in many cases, eliminating the need for wired connections (Huang et al., 2018). A limited battery capacity and long charging times were weak points of AGVs and reduce performance, utilization, and computational power. In addition, traditional lead-acid high-capacity batteries required increased vehicle size. The new high-capacity batteries (e.g. lithium-ion) enable longer operational time and provide more power for the calculations needed for autonomous navigation and operations. They also allow the AMRs to be smaller (this also holds for the newest AGVs) and thus to be deployed in narrow-aisle areas, or even directly underneath multiple loads stored closely in deep lanes (Lamballais et al., 2017). With these technological improvements, the importance of battery management has declined somewhat, although it may still be relevant in 24/7 operations (Zou et al., 2018). By contrast, reliable system operations, including battery management, have gained research interest. In addition, the increased battery power encourages more intensive scheduling decisions.

2.1.4. Manipulating equipment

By combining AMRs with different manipulating equipment into a single unit, new services and material handling operations can be performed. Robotic manipulators enable AMRs not only to lift unit loads but also to pick single items (Shah et al., 2018). AMRs can collaborate with humans and other AMRs, to carry out transportation tasks jointly (Lee & Murray, 2019; Machado et al., 2019). The extended range of operations that AMRs offer must be planned over both the short and long term. This includes making new decisions on how to provide these services, developing methods on how AMRs can collaborate, and integrating their scheduling with production schedules to ensure collaboration at the right time and place.

2.1.5. Processing devices

The AMR's ability to navigate and operate in a dynamic environment results from its capacity to make real-time decisions. Previously, intelligent decision-making capabilities in mobile robots were limited because of the significant computational power required. With the introduction of ultra-low-power AI processors, real-time decision-making for AMRs became possible (Kim et al., 2017). Today, powerful AI-focused processor architectures such as the Intel Nervana, NVIDIA Xavier and Kneron AI SoC are widely available for vision recognition of face, body, gesture, object, or scene. This development especially affects the operational level of decision-making in AMRs. Enabling calculations of complex decisions allows new ways of dynamic routing and scheduling, navigating and classifying, and reacting to obstacles appropriately.

2.2. Software

2.2.1. Simultaneous localization and mapping

SLAM, which is a supportive technology for real-time navigation, encompasses the two activities of creating detailed area maps of the environment and calculating the position of an AMR on a map (Bloss, 2008). The mapping process converts 3D point clouds retrieved from the scanning sensors to a reference map while filtering the dynamic obstacles. Combining the sensing information to accurately determine the AMR's location at any time has proven to be a difficult challenge. In recent years, a breakthrough was made through the application of Kalman filter technology. Estimations from different sensor sources must be combined to generate a probability distribution over all possible robot locations and to predict a robot's position and orientation (Bloss, 2008). The Kalman filter uses a recursive algorithm to correct the prediction over time. Using several measurement sources, measurement

noise and sensor inaccuracy issues can be overcome (Pratama et al., 2016). For high accuracy and reliability, SLAM can be supported indoors by real-time location systems using ultra-wideband technology, and outdoors by global positioning systems using network satellites placed in orbit. Applying trilateration and multilateration allows the identification of the exact positions of the AMRs.

2.2.2. Motion planning

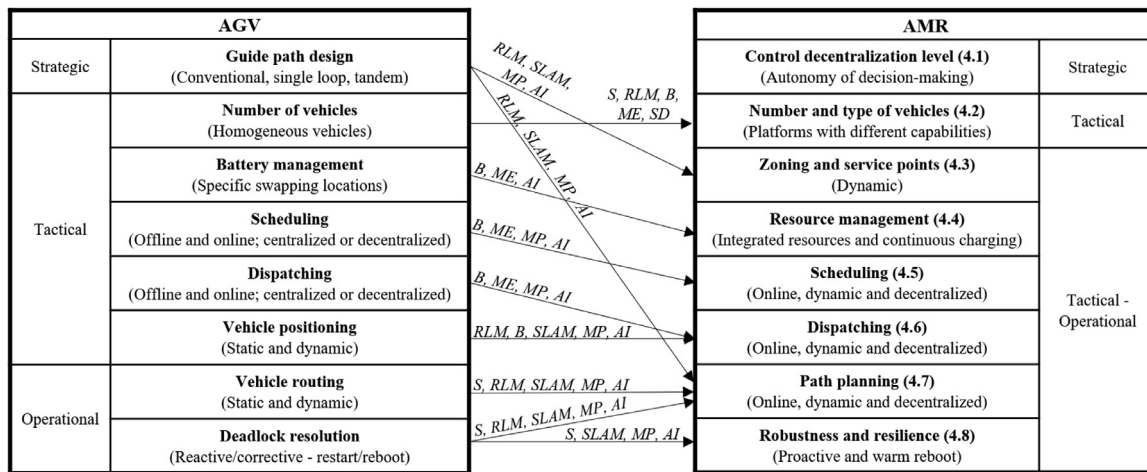
Motion planning is an essential part of the vision-based guidance systems and manipulation of equipment. Using the input of the environmental representation, the motion planner can calculate the robot's size and dynamics and a feasible, collision-free path from the initial point to the final position (Karaman & Frazzoli, 2011). Further, the motion planning algorithms provide speed and turning commands to the vehicle actuators such as wheels or manipulator to reach the set of guidance points along the path. Sensors and the SLAM technology allow the AMR trajectory to be tracked and provide feedback to correct its position. In dynamic environments, the motion planner allows the AMR to adapt to traffic or congestion by reducing speed, or even by stopping the vehicle. If planned paths are no longer feasible due to an emerging obstacle, a new collision-free path will be generated. Decisions that must be made about the guide path, routing, and obstacle avoidance are all taken by the AMR itself. Several open source platforms provide codes for the control of AMRs (and other robots). Examples include Robotics and Autonomous Systems by Intel (<https://01.org/robotics-autonomous-systems>), the Robot Operating System (<https://www.ros.org/>), Yet Another Robot Platform (<https://www.yarp.it/>) and the Mobile Robot Programming Toolkit (<https://www.mrpt.org/>).

2.2.3. Artificial intelligence

Facilitated by hardware developments, AI techniques can be applied to support AMRs in both navigation and providing services. Compared to AGVs, for which most situations and tasks are predictable and therefore solvable by predefined decision rules, AMRs navigate autonomously in a dynamic and unpredictable environment. AI techniques such as vision systems and machine learning (ML) enable the identification and classification of obstacles. Fuzzy logic, neural networks and neuro-fuzzy and genetic algorithms are examples of well-known fusion techniques that help move the robot from the starting point to the target, while avoiding collisions with any obstacles along its path (Almasri et al., 2016; Dias et al., 2018). These techniques are inspired by the ability of the human brain to perform complex tasks by reasoning about, and adapting and responding to changes in the environment. Such behavior-based learning methods can be used to solve complex control problems that autonomous robots encounter in an unfamiliar, real-world environment. Without these techniques, AMRs would react to all obstacles in the same way. The introduction of AI affects all decision areas by opening new approaches to making decisions. The AI branches of vision, ML and planning, have been found to be very promising. As AI continues to advance, the ability to interact and collaborate with AMRs will increase. For example, in warehouses in which a human in the picking role and an AMR in the fetching role collaborate in order picking (Fig. 3 (i)), the human picker can use speech or gesture instead of tactile communication to confirm that picking tasks have been completed or to ask for help in finding items.

3. Planning and control framework for AMRs

The new developments and possibilities of AMRs, compared to AGV systems, require a new decision-making framework for planning and control.



Hardware - S: Sensors, RLM: Robot Locomotion Mechanism, B: Battery, ME: Manipulating Equipment, SD: Semiconductor Devices.
Software - SLAM: Simultaneous Location And Mapping, MP: Motion Planner, AI: Artificial Intelligence.

Fig. 4. Impact of technological developments on planning and control decision areas for AMRs.

The central hierarchical system has been challenged by large fleet sizes or fleet swarms, collaborative robots, and an increased variety of services provided. System performance is reduced by a centralized control hierarchy since it must take and simultaneously communicate many decisions in a short period. For instance, in robotic mobile fulfilment (RMF) systems (Fig. 3 (g)), there can be hundreds of mobile robots forming a large system (Wang et al., 2020). The largest Amazon warehouses control thousands of mobile robots. Such systems are often divided into modules that consist of pods positioned in a grid structure, picking and replenishment stations, and vehicles (Lamballais et al., 2020). The system can easily be scaled up by adding vehicles or modules. In such intralogistics environments, decentralized control of navigation and task allocation can help to handle the high number and density of vehicles by reducing elevated levels of traffic and congestion. The degree of decentralization of operations and the responsibility of the AMRs must be decided at the strategic level.

Depending on specific tasks and applications, the number of AMRs, including equipment such as manipulators, must be determined. Methods need to be developed for deciding and evaluating the fleet's size and equipment in terms of flexibility, productivity, quality, and costs. However, due to the short implementation times of systems, once they are available, vehicles can be added on the spot.

AMR vehicles are no longer tied to a fixed guide path, but instead can plan their path themselves and so freely move in pre-defined travel zones. The design of a guide path is therefore no longer necessary, but new decisions such as defining zones in which AMRs can operate autonomously must be taken (Fig. 2). These zones can be defined and changed on a daily or weekly basis, or dynamically in a decentralized manner by the AMR. The speedy establishment and easy change of zones enables operational flexibility that keeps AMR responsiveness high. Within these zones, service positions for tasks such as picking items or collaborating with humans can simply be added, assigned, or configured on a short-term basis. The zones can provide travel directions, traffic levels and other relevant information to reduce congestion and the risk of accidents. Both the service zone and service point locations have a strong impact on travel times and lead times. The increased flexibility requires new principles for scheduling and dispatching and how to allocate idle AMRs for maximum responsiveness.

The robot's locomotion mechanism and equipment enable the AMRs to follow paths and handle materials that AGVs cannot.

AMRs can coordinate with multiple robots to reduce traffic (e.g. in a RMF system), to climb shelves (e.g. in some Autonomous Vehicle Storage and Retrieval (AVS/R) systems, see Fig. 6(o)), or to remove blocking loads (e.g. in Puzzle-Based Storage (PBS) systems, see Fig. 3(n)) to retrieve or store unit loads. This navigation flexibility must be incorporated in path planning approaches.

Like all intralogistics vehicles, AMRs must adhere to many standards, e.g. safety standards, before they can be brought to market. They must also be robust and reliable. Currently, AGV systems cannot work without human surveillance and support. Their sensitivity to a dynamic environment forces strong focus on error and failure management by humans. AI can support the recovery of AMRs after failures and find strategies to overcome such errors, making them more robust.

Changes in the planning and control environment from hardware and software developments have changed the traditional AGV decision areas to the following ones for AMRs (Fig. 4): (i) the control decentralization level, (ii) the number and type of vehicles, (iii) zoning and service points, (iv) resource management, (v) scheduling, (vi) dispatching, (vii) path planning and (viii) robustness and resilience.

The emerging planning and control framework with its decision areas is presented in the next section. In each section, first, we explain the shift from AGVs to AMRs and the corresponding decision problem. Second, we present and discuss the modeling approaches for AMRs and the AGV methods applicable for AMRs as per the literature.

4. Methods for planning and controlling AMRs

4.1. Control decentralization level

Problem

The level of control decentralization is a fundamental strategic decision. Determining which parts of a system should be controlled in a centralized or decentralized manner plays a crucial role in defining the interfaces between AMRs and their operating environment.

Centralized control structures are deeply rooted in the industry and can access global information to achieve optimal single-objective performance for small-scale, simple systems. Decentralized control can often access only local information and find local optimal solutions for systems with multiple objectives, that

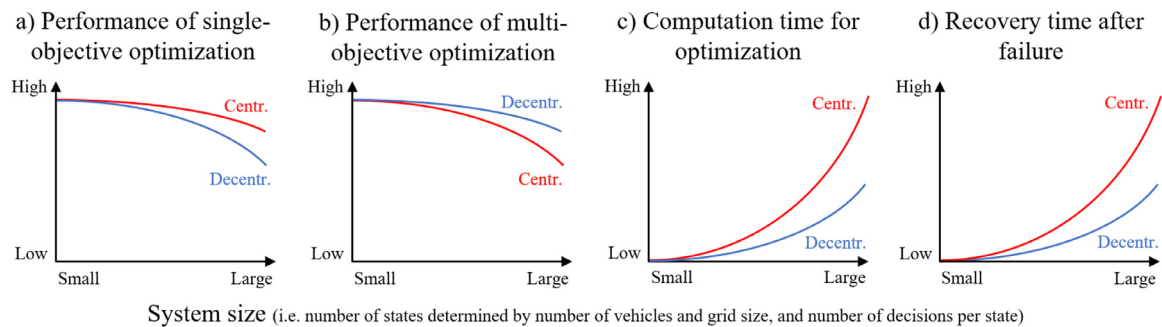


Fig. 5. Centralized versus decentralized control in small and large systems (partly based on Fauadi 2012).

are globally suboptimal (Fig. 5a). However, large-scale, complex systems require decentralized systems (De Ryck et al., 2020a).

With a greater variety of operations and a more unstructured environment, decentralized control can achieve high performance, since multiple criteria are included in the optimization (Fig. 5b). Large systems with many vehicles imply a large number of decision states to be considered in the optimization approaches. The computation time is significantly lower in decentralized than in centralized control, since the decision making is distributed among multiple AMRs taking only local factors into consideration (Fig. 5c). This also allows further reduction of the recovery time after failure (Fig. 5d). Centralized control on the other hand requires a long time to evaluate the state of every single AMR after failure and to coordinate the entire fleet to recovery. Therefore, it is crucial, at the strategic decision level, to provide methods to determine the most suitable control decentralization level for the different decisions area such as scheduling, zoning or path planning.

Methods

AMRs with varying degrees of decentralization have been introduced and discussed in existing studies. Wan et al. (2017) introduce a cloud-based decision-making engine with centralized scheduling (i.e. task allocation) and decentralized navigation (i.e. map processing) that can be shared among AMRs. The small system size facilitates more central control of AMRs and decisions can be made by the cloud-based system. The study emphasizes that applying simple AMRs, and outsourcing the decision making to the cloud can keep overall costs low, while simultaneously using simulation modeling based on the AMRs' statuses and locations can improve their energy performance.

Simulations and computational experiments have been used to analyze the pertinence and feasibility of hierarchical control of AMRs (Demesure et al., 2017; Zhang et al., 2017). Kousi et al. (2019) apply discrete event simulation to analyze the performance of an assembly line in the automotive industry. Under their approach, centralized cloud-based systems can detect material supply requirements, trigger material supply operations, schedule them, and communicate schedules to the AMRs. This reduces the frequency of parts depletion and limits vehicle travel distance, leading to increased assembly line productivity and efficient resource utilization. In high-density, PBS systems, mobile robots can autonomously move storage loads from input points to the storage area or retrieval loads from storage to output points (Gue & Kim, 2007; Alfieri et al., 2012; Gue et al., 2014). These systems do not have travel aisles: the robots must collaborate to move loads out of the way to create paths. The robots negotiate and divide the transportation tasks to move items quickly and deadlock-free.

A few studies have investigated the decentralization of control areas beyond path planning. AMRs can be a cost-effective alternative compared to other material handling systems and allow quick implementations. De Ryck et al. (2020a) describe a decentralized task allocation in which AMRs can negotiate with or bid against other machines for task assignments. Fragapane et al. (2020b) use

mathematical modeling and parametrical analysis to determine optimal configurations and the associated throughput performance impact of the AMR in production networks when compared to traditionally balanced lines. The control of connecting workstations during workstation downtime within a production network relies on AMRs.

The studies by Maniya and Bhatt (2011) and Hellmann et al. (2019) offer further support by using new methodologies to consider and select centralized or decentralized control systems. Maniya et al. (2011) propose a modified grey relational analysis method combined with an analytical hierarchy approach for multi-attribute selection processes. Hellmann et al. (2019) introduce a novel framework that integrates failure modes and effects analysis and analytic hierarchy processes to support decision-making for AMR design, operation, and control policies.

In the analysis of centralized and decentralized control structures, the prime objectives are to maximize resource utilization and throughput while reducing costs. The most common trend is to decentralize decision-making for navigation, but several other decision areas can also be decentralized and thus increase the autonomy of AMRs. Every application area has unique needs and requires a tailored mix of centralized and decentralized control. The degree of autonomy in AMRs must be analyzed and determined at the strategic level to establish a reliable basis for the number of vehicles and other relevant requirements.

4.2. Number and type of vehicles

Problem

Combining the analysis of both the distances in the fixed guide path and the number of trips with AGV characteristics traditionally supported decisions on fleet size. However, due to the navigational flexibility of AMRs, travel distances and times between service points are highly variable or even uncertain. While AGV routing only has a limited number of possibilities to connect two points within the guide path, the autonomous path finding mechanism that AMRs use means the possibilities are effectively endless. AMRs currently operate in application areas in which humans, such as hospital visitors, may be unfamiliar with AMR tasks. Congestion and high traffic are unavoidable, which will hinder AMR performance and increase travel time. Thus, new methods are needed to calculate the right number of vehicles. The flexible platform also enables different types of AMRs that vary by equipment, size, or function within a single fleet. The number of vehicles and the type of equipment must also be determined at the tactical level.

Methods

Mathematical modeling and simulation

Simulation and mathematical modeling can be used to determine the optimal number of vehicles in manufacturing. Ji and Xia (2010) apply discrete event simulation to find the number of vehicles required for high utilization and to guarantee the stability of a system with a varying number of depots. Singh et al. (2011) use

discrete event simulation to find the minimum number of vehicles needed to meet the entire material distribution requirement in a manufacturing system. To investigate different layout configurations in warehouses, [Vivaldini et al. \(2016\)](#) and [Ribino et al. \(2018\)](#) employ discrete event simulation and agent-based simulation to analyze throughput performance and to derive the optimal number of vehicles. [Gharehgozli et al. \(2017\)](#) apply simulation in a game theoretic setting to allow decision makers to understand the relationship between costs, throughput time, and waiting time when determining the optimal number of autonomous vehicles for transport between container terminals.

To ensure low traffic volumes, [Małopolski \(2018\)](#) and [Lyu et al. \(2019\)](#) model manufacturing environments and apply simulation to determine the optimal number of vehicles by simultaneously considering scheduling, path planning, and conflict-free vehicle routing. [Draganjac et al. \(2020\)](#) analyze the impact of traffic conflict negotiation in industrial logistics on throughput performance in a simulation model to determine the right number of vehicles.

A different approach is offered by mathematical programming models. [Pjevcevic et al. \(2017\)](#) propose a data envelopment analysis decision-making approach to simultaneously determine vehicle numbers, reduce operating delay costs, and increase equipment utilization rates in container terminals. Most studies focus on homogenous fleets, but the AMR's flexible platform allows for heterogenous fleets in which AMRs have different or exchangeable equipment. Collaborating pickers and fetchers (mounted on the same vehicle base) in a warehouse context offer an example. A recent study by [Lee et al. \(2019\)](#) proposes a mixed-integer linear programming (MILP) approach and numerical analysis to determine the number and type of vehicles needed to minimize the time required to pick and transport all items on a pick list from the warehouse to the packing station.

Queuing network modeling

In queuing network modeling, a customer arrives in a queue and goes through several service processes in a network, according to some routing mechanism, until he exits the system. The AMRs can be modelled as a server (open queuing network) or customer (closed queuing network) or to connect to a customer for specific tasks (semi-open queuing network). The different models have different application possibilities. While open queuing networks can be used at the operational decision level to estimate waiting and throughput times. Closed queuing networks assume the system is the bottleneck and as such they are fit to estimate throughput capacity of a given configuration at design decision level. Semi-open queuing networks can do both, but the (approximate) analysis is somewhat more involved.

[Fukunari and Malmberg \(2008\)](#) use an open queuing network model to estimate the cycle time and resource utilization for AVS/R systems. Performance is estimated using an iterative computational scheme considering random storage assumptions. [Yuan and Gong \(2017\)](#) determine the optimal number and velocity of robots and provide design rules for RMF. [Wang et al. \(2020\)](#) apply analytical models, including a bottleneck-based model and an open queuing network model, to simulate robotic mobile fulfilment system layout configurations and to identify the optimal number of vehicles. [Zhang et al. \(2020\)](#) use open queuing networks and discrete event simulation to investigate the influence of robot capacity on the performance of a flexible flow shop with random and state-dependent batch transport. Open queuing networks cannot model a joint capacity constraint set by the AMRs involved in multiple processes.

Limiting the number of resources, as in closed queuing network, allows to focus on the population constraint. [Fukunari and Malmberg \(2009\)](#) propose a closed queuing network approach for estimating resource utilization in AVS/R systems. [Hoshino et al. \(2007\)](#) propose using closed queuing network model and simu-

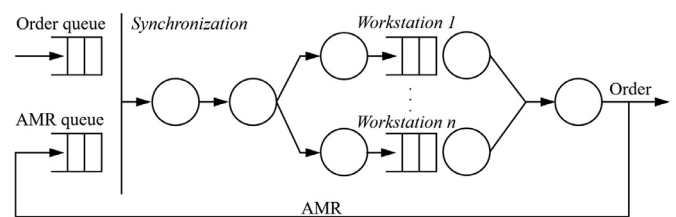


Fig. 6. Semi-open queuing network model with AMRs.

lation to analyze the transportation system within container terminals. The suitable number of vehicles can be determined that minimizes total investment cost. [Chooibneh et al. \(2012\)](#) propose an analytical multi-class closed queuing network model, extended with simulation, to determine the optimal number of vehicles and the ratio between loaded and empty travel times to maximize system throughput in a manufacturing or distribution environment. [Roy et al. \(2016\)](#) also apply a closed queuing network model with simulation to investigate the effect of traffic on the number of vehicles in container terminals. [Roy et al. \(2020\)](#) use open, closed, and semi-open queues to determine the numbers of vehicles with different capabilities in automated container terminals. The results of these studies indicate that vehicle congestion and speed depend heavily on the number and type of vehicles and throughput.

Semi-open queuing network modeling combines the advantages of open queuing networks (external queue to accommodate jobs whose entrance is delayed) and closed queuing networks (inner network with a population constraint). Using a synchronization station, incoming customers waiting at an external queue can be paired with available resources in the resource queue (Fig. 6).

This modeling approach allows to capture the external waiting time and precisely estimate the throughput time. The network is typically aggregated to a single synchronization station plus one station with queue, representing the remaining network, with a load dependent service rate. The continuous-time Markov chain of this network is analyzed. After determining the generator matrix

$$Q = \begin{pmatrix} B_0 & C_0 & 0 & 0 & \dots \\ A_1 & B_1 & C_1 & 0 & \dots \\ 0 & A_2 & B_1 & C_1 & \dots \\ 0 & 0 & A_2 & B_1 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

which is nearly block-tridiagonal and which includes a repetitive pattern of the matrices A, B, and C, the matrix-geometric method can be applied to solve for the state probability vector π of the system (solving for $\pi Q = 0$ with $\pi 1 = 1$) and from that performance measures can be calculated. To solve for π the so-called rate matrix R must be calculated from the equation

$$C_1 + RB_1 + R^2A_2 = 0,$$

which includes the repetitive part of the generator matrix Q . R can be calculated iteratively ([Neuts, 1981](#)), and the rate matrix at the n -th iteration is given by $R_{(n)} = -(C_1 + R_{(n-1)}^2A_2)B_1^{-1}$. The iteration process stops when the difference of two consecutive iterates is less than a given tolerance of $\|R_{(n)} - R_{(n-1)}\| < \varepsilon$. This rate matrix R allows one to obtain all the stationary probability vectors, facilitating the network analysis with relative high accuracy.

The studies by [Ekren et al. \(2013, 2014\)](#) demonstrate that AVS/R systems can be modelled efficiently as a semi-open queuing network. The performance of the external queue length as well as the average number of transactions in the network (including waiting for service, average number of vehicles in the vehicle pool, and average waiting time in the external queue) can be evaluated by applying the matrix-geometric method and the proposed extended algorithm ([Ekren and Heragu 2010](#)). The study by [Zou et al.](#)

(2016) applies semi-open queuing networks to estimate the system throughput time and cost and determines the number of robots which have transport and lifting capabilities and can move on the grid roof of a compact warehouse.

In sum, mathematical optimization, simulation, and queuing networks have all shown to be suitable methods to model the industrial environment with its specific constraints, to analyze operating systems and to evaluate the number of vehicles, with maximizing system throughput as main objective and workload distribution, minimizing throughput time, travel time, and costs as additional objectives.

4.3. Zoning and service points

Problem

The transition from providing services along fixed guide paths to flexible areas requires decisions to be made regarding the design of zones and service points. In some AMR application areas, the number and location of service points can be decided dynamically. Examples include guidance assistance in hospitals or shopping malls and RMF systems or collaborating fetchers in warehouses. Dividing the service areas into several zones with single or multiple vehicles can improve cost and productivity performance. Limiting the operating area for each vehicle improves the overall responsiveness of the system, since only short trips are performed, and vehicles are available more quickly. Therefore, zoning comprises the activities and decisions involving (I) analyzing the area in which the service must be provided, (II) determining fixed and/or dynamic service points, (III) configuring zones (adding, removing, dividing or overlaying zones, and defining flow direction) and (IV) determining the number of vehicles in each zone. The sequence of these steps can vary.

Methods

Several studies suggest designing zones in loops or blocks and co-locating picking and delivery points to improve performance within manufacturing systems. Shalaby et al. (2006) investigate zone partitioning and the selection of a tandem transportation system, using a heuristic algorithm to meet several objectives: minimizing total flow distance and total handling cost, achieving maximum workload, and limiting the number of between-zone trips. Asef-Vaziri et al. (2007) develop exact optimization, decomposition, and heuristic procedures to design a unidirectional flow loop. A binary integer programming model and a neighborhood search heuristic method support maximizing loaded-vehicle trips and minimizing empty vehicle trip distances. Farahani et al. (2007) investigate the flow path layout and develop a genetic algorithm to determine the optimal location of the loop and the picking and delivery stations, with the goal of minimizing the total distance travelled. ElMekkawy and Liu (2009) use a memetic algorithm in a computational experiment techniques to optimize the partitioning problem in a tandem AGV system, by minimizing overall workload, balancing the workload across zones, and preventing bottlenecks. Hamzei et al. (2013) propose a cutting-plane algorithm to model and design the flow path and the location of pickup and delivery points. Asef-Vaziri and Kazemi (2018) investigate the traveling salesman problem of the shortest loop covering at least one edge of each workstation. Their proposed evolutionary algorithm achieves robust loop design solutions that maximize loaded and minimize empty vehicle travel.

Analyzing different layouts and zone configurations simultaneously can yield additional performance improvements. Using a simulated annealing approach, Tubaileh (2014) analyzes different manufacturing systems with simulations to find the optimal locations for machines in all feasible layouts. The objective of the study is to minimize travel times in a material handling system. Qi et al. (2018) investigate warehouse layouts and develop zones

according to task density. Their simulation supports minimizing total traveling time, total distance traveled, and total waiting time. They recommend an even storage distribution of fast-selling or frequently transported goods to improve system performance. According to Lee et al. (2019), zoning in warehouses can significantly reduce costs. Different warehouse layouts, zone and service point configurations for order-picking robots are analyzed using MILP and numerical analysis with the goal of minimizing the time needed to deliver all items from a pick list to the packing station. Lamballais et al. (2017) and Roy et al. (2019) use queuing network models and simulation to analyze zone assignment strategies in RMF systems to improve system throughput, average order cycle time, and robot utilization. To analyze the preferred number of service points in such systems, Lamballais et al. (2020) use a semi-open queueing network with simulation to determine the optimal number of pods, and picking and replenishment stations. With regard to AVS/R systems, Roy et al. (2012) propose a semi-open queueing network approach to investigate the impact of vehicle locations and zones within a tier using multiple vehicle classes and class switching probabilities in terms of throughput performance. Azadeh et al. (2020) use a closed two-phase server queueing network, embedded in a Markov decision process, to dynamically adjust the number of zones in a human-robot collaborative picking system. They show that dynamically adjusting the number of zones can lead to higher throughput capacity in multichannel warehouses with varying numbers of large and small orders.

Differences in zoning and in the number of vehicles per zone can influence overall traffic. Reducing congestion between vehicles – by reducing the time that vehicles spend negotiating complex traffic situations and removing bottlenecks in high-traffic areas – helps to decrease overall travel time and increase system responsiveness. Ho and Liao (2009) propose a dynamic zone strategy that includes zone partition design and dynamic zone control. Their simulation results show a reduction in vehicle congestion and an increase in load balance between vehicles in different zones. Azadeh et al. (2019b) use closed-queueing network models to compare different zoning schemes and access control rules to estimate the throughput impact on vehicle blocking. To maximize throughput, Singh et al. (2011) suggest using discrete event simulation and a scheme for partitioning the entire area into exclusive zones for individual vehicles in an automotive manufacturing plant. Małopolski (2018) offers a method that divides the layout into a rectangular grid and then uses both linear programming and simulation to improve transportation performance for unidirectional, bidirectional, and multiple-lane flow path systems in a manufacturing environment.

The main objectives when designing zones and service points are to minimize travel distance, traffic, and throughput time while distributing the workload throughout the system, to increase and – ideally – maximize system throughput and resource utilization. Dynamic zones with multiple and varying service points increases the AMR modeling complexity and limits the application of earlier AGV-based approaches. When service point positions change dynamically, they impact the workload and service demands. This increases the number of variables in mathematical models, with negative consequences for feasibility and on computation time. Evolutionary approaches and simulation seem to be most suitable in these cases. Another promising approach has been used to model the assignment of mobile robots in warehousing. In warehouses, the service points (picking locations) are numerous and they change according to the orders to be fulfilled. Queuing network modeling (to estimate performance) and Markov decision processes (to assign vehicles dynamically) are a promising combination of methods able to solve complex and dynamic problems in an accurate way and with acceptable computation time. They can be applied also in other application areas, such as manufacturing,

hospitals or shopping malls, adjusting the definition of the service points to the application context. These methods are also suitable to dynamically manage large amounts of input data. Further extensions will be to integrate the traffic modeling into these methods in order to consider blocking and congestion and their impact on the performance of the system.

4.4. Resource management

Problem

Current AGVs can only provide few handling activities (e.g. lifting and moving), since they are equipped with only a single handling unit (e.g. lifting unit). However, in robotics and flexible manufacturing, it is common to exchange equipment. AMRs can load, use, unload, exchange equipment, and charge or exchange batteries. The AMR's platform allows a wide range of resources to be used and shared. The decision-making processes of location planning, scheduling, and dispatching these resources are essential to their optimal utilization and thus to high AMR productivity performance.

Methods

Even though the energy density of batteries is increasing, it is still necessary to decide where charging stations should be located. [Boysen et al. \(2018\)](#) investigate the influence of battery capacity, the number and location of charging stations, and charging periods on makespan performance. They propose a genetic algorithm and computational experiments to identify the optimal charging locations in terminals. A study by [Kabir and Suzuki \(2019\)](#) explores how the four heuristics of (I) selecting the nearest battery station, (II) selecting a battery station that will cause minimum delay considering both travel time and waiting time in a queue, (III) selecting the nearest battery station on the current route and (IV) selecting the farthest reachable battery station on the current route, can affect performance in terms of total travel distance and waiting time at a battery station. Their simulation reveals that a higher frequency of decision-making about battery swapping helps to increase the productivity of a manufacturing system. [Zou et al. \(2018\)](#) evaluate battery charging and swapping strategies in an RMF system. Applying a semi-open queuing network and simulation allows the comparison of different strategies in terms of cost and throughput time performance. The study emphasizes that throughput time performance can be significantly affected by the battery recovery policy that is selected, and that inductive charging offers the best performance. [De Ryck et al. \(2020b\)](#) propose a decentralized charging approach in which an AMR can independently choose when to visit a charging station and how long to charge. Their approach is modeled as an extension of the traveling salesman problem in manufacturing systems and solved by a general constrained optimization algorithm. They investigate different charging schemes and charging station choices to increase resource efficiency.

In the near future, the efficient management of resources will play a greater role in planning and controlling AMRs. While AGVs employ a narrow range of handling equipment, AMRs will have access to and use a wide variety of equipment, which requires efficient management and use. Fully decentralizing resource management to the AMRs, without some form of coordination, will lead to suboptimal results at the system level. Iterating the decentral optimization decisions for all AMRs and sharing the results between multiple units are essential to achieve a near global optimum. Using the results of the decentralized decisions in operational level to take tactical decisions such as location planning of battery stations or equipment storage areas can yield in performance such as short travel time. New modeling approach for AMRs are needed to solve these decisions simultaneously or iteratively. Predictive analytics can further support in deciding when to charge batteries or

when to exchange the mounted equipment to a time period with lowest risk of conflict. None of the current studies are providing methods which consider the operational information exchange for such decisions.

4.5. Scheduling

Problem

A substantial body of literature has been developed to support the decision-making process in scheduling material handling systems simultaneously with machines, humans, equipment, parts, and containers. In manufacturing, most studies consider a low number (fewer than 50) of vehicles under centralized, hierarchical control applying mixed integer programming models with heuristic algorithms. Mathematical modeling and optimization approaches have been widely developed to solve scheduling problems, mostly in manufacturing since the number and type of tasks are typically higher than in a warehouse. Some of the papers have also integrated simulation models to validate and generalize their results. A new stream of research uses AI techniques, such as evolutionary algorithms, which is now possible due to the advances in computational power. However, decentralized scheduling methods in which AMRs negotiate or bid for tasks are still scarce.

Methods

Mathematical modeling for scheduling of transportation activities

The scheduling of 'only' vehicles has been studied by analyzing the impact on the performance of the manufacturing system. Few papers have focused on container terminals and warehousing, since solving dispatching problems seems to be predominant in these application areas.

In manufacturing systems, decomposition methods ([Corréa et al., 2007](#)) and mathematical and statistical models ([Ghasemzadeh et al., 2009](#)) have been used to solve and analyze the interaction between conflict-free vehicle routing and scheduling policies and the impact on the production delays. Other authors have studied the impact on makespan, cycle time deviations, and vehicle earliness and tardiness, through two-step algorithms to cluster the solution space and next to find the optimal solution ([Fazlollahtabar et al., 2015](#); [Bakshi et al., 2019](#)). For more complex problems with heterogeneous and multiple-load vehicles, simulation is used to evaluate different scheduling policies ([Ho & Chien, 2006](#); [Bocewicz et al., 2019](#)). In container terminals, scheduling transportation activities has been modeled by a minimum cost flow model solved by an extended simplex algorithm and greedy vehicle search ([Rashidi & Tsang, 2011](#)). [Polten and Emde \(2020\)](#) focus on warehouses with very narrow aisles and address the multi-aisle access scheduling problem by proposing two access policies: exclusive and parallel access. A MILP and a large neighborhood search algorithm analyze and optimize the robot task allocation problem.

Methods for joint scheduling of vehicles and machines

The simultaneous scheduling of jobs in machine centers and vehicles is relevant to obtain high overall efficiency in the manufacturing system. The main objectives are to minimize the makespan, waiting times, and transportation costs. Due to the complexity of the problem, general heuristics, decomposition algorithms, adaptive genetic or memetic algorithms, and simulated annealing approaches are mainly applied ([Jerald et al., 2006](#); [Deroussi et al., 2008](#); [Nishi et al., 2011](#); [Lacomme et al., 2013](#); [Zheng et al., 2014](#); [Baruwa, 2016](#); [Lei et al., 2019](#)). [Fazlollahtabar \(2016\)](#) and [Fazlollahtabar and Hassanli \(2018\)](#) apply a mathematical cost flow model and modified network simplex algorithm, while [Lyu et al. \(2019\)](#) use simulation to investigate the impact of scheduling policies on makespan and vehicles utilization. In the context of a container terminal, [Yang et al. \(2018\)](#) analyze simultaneous scheduling of multiple cranes and vehicles at a container yard to minimize the

makespan of container loading and unloading by using a genetic algorithm. [Chen et al. \(2020\)](#) propose a multicommodity network flow model to deal with inter-robot constraints that accurately reflect the complex interactions among container terminal agents. Using a genetic algorithm, the average makespan of the system and the average resource transfer times of all robots can be minimized.

AI-based methods for multi-objectives or constraint problems

Due to advances in computational power and the application of AI techniques, the use of multi-objective or constraint scheduling models has become more feasible, in particular in complex environments, such as manufacturing with multiple jobs and machine centers. Some authors have developed genetic and ant colony optimization algorithms ([Udhayakumar & Kumanan, 2010](#); [Saidi-Mehrabadi et al., 2015](#)), or a sheep flock heredity algorithm ([Anandaraman et al., 2012](#)), hybrid evolutionary or genetic algorithms, particle swarm optimization ([Gen et al., 2017](#); [Mousavi et al., 2017](#); [Rahman et al., 2020](#)), and a whale optimization algorithm ([Petrović et al., 2019](#)). The whale optimization algorithm is inspired by humpback whale hunting. It first explores the ‘ocean’ looking for ‘prey’ (exploration phase). This corresponds to agents searching the state space by changing their locations while attempting to find global optima. When a location near a global optimum is found, they stop. After the first phase, the whales start diving in a spiral shape in order to trap the prey. This is called exploitation phase. In the algorithm, the agents follow a ‘leader’ and change their locations according to a shrinking encircling mechanism, while updating their location data, until the final location. These methods perform well for solving multi-objective problems, combining e.g. minimization of makespan, travel time, and tardiness, with maximization of battery charging efficiency and vehicle utilization.

Methods for decentralized scheduling and task allocation

Current information sharing and computing technologies provide a new information processing method for online machine and vehicle scheduling, enabling new dimensions of agility and flexibility. High levels of connectivity and communication are needed when decentralizing task allocation. [Zeng et al. \(2018\)](#) propose a collaborative and distributed scheduling approach for decentralizing task allocation, based on dynamic communication between vehicles and machines, using a hormone-regulation mechanism. A new promising approach in decentralized scheduling is offered by auction-based methods where an announcer (machine) and bidder (AMR) cooperate to achieve high performance in task allocation. [De Ryck et al. \(2020a\)](#) classify different auction-based methods for task allocation in single, bundled, and combined items offered and bid on these in sequential or parallel auctions. The bid calculation is a crucial element since it reflects the cost for the AMR to perform the specific task, and therefore for scheduling and task allocation. Even while executing a given task, AMRs can bid on new tasks and thus locally optimize the task list and use this information to calculate the next bid. Bids can be calculated based on the cost to perform the tasks by the AMRs, or on the marginal cost considering also the other tasks in the list. Each type of calculation has its most suitable bidding algorithm. For the first type of cost CNET, OCA-Alloc, CBAA and CBBA are used, while marginal cost is used in Prim Allocation, SIT- and SET-MASR algorithms (see [De Ryck et al. 2020a](#) for an overview). These action-based methods overcome the limitations of previous OR approaches, and extend to large vehicle fleets, while introducing flexibility and scalability. The computation is distributed, so it can be applied to very complex problems with many constraints. The collateral effect is the increase in demand for computational power for each single AMR, with negative impact on battery consumption. Further opportunities for improving these methods will be in the integration of this decision area with resource management and dispatching.

4.6. Dispatching

Problem

Smart dispatching methods, that allow AMRs to be close to the point of demand before an actual need is announced, can increase performance. The increased flexibility of accessing a wide area and of free positioning due to autonomous navigation, enable new opportunities for positioning and for cruising while an AMR is idle. Centralizing the decision-making processes of distributing and dispatching AMRs requires a system that analyzes the AMR positions and the demand data. ML and big data analysis of demand can support the optimization of vehicle distribution over the system. However, large-scale AMR systems need high computational power to analyze and communicate in real time. Decentralizing this process will decrease the need for high-power cloud computing. Each AMR will optimize its available time based on historical data and on data shared with neighboring AMRs. Continuous communication and negotiations will optimize the AMR's ability to react quickly to demand.

Methods

Various multi-attribute dispatching rules have been developed to allocate tasks to the appropriate AMRs, using mainly mathematical modeling, queuing networks, and simulation to evaluate them. They have been mostly applied in manufacturing, and only few implementations can be found in warehousing and container terminals.

Several mathematical approaches have been developed to model the dispatching problem in its complexity, including path layouts, vehicle capacity and restrictions as constraints, and single or multiple objectives, such as minimizing makespan, travel time, and delay. [Ventura and Rieksts \(2009\)](#) develop a dynamic programming algorithm to solve idle vehicle positioning in a single loop AGV system. [Ventura et al. \(2015\)](#) extend the problem to a general guide-path layout, solved by a genetic algorithm. [Bozer and Eamrungrroj \(2018\)](#) present an analytic model to assess the throughput performance and device utilization of various dispatching rules, by varying layout configurations in trip-based systems. In case of more complex problems, with multi-objectives and more constraints, heuristics like genetic and evolutionary algorithms have been implemented ([Lin et al., 2006](#); [Umar et al., 2015](#); [Miyamoto & Inoue, 2016](#); [Gen et al., 2017](#)).

While queuing network modeling is less often applied to manufacturing systems, it is commonly used in warehousing, in particular for RMF systems. An extended review of closed queuing network models by [Smith \(2015\)](#) analyzes optimal workload allocation in manufacturing systems with multiple transportation servers, infinite-capacity workstations, and a finite capacity state. [Zou et al. \(2017\)](#) apply semi-open queuing networks and a two-phase approximate approach to estimate the performance of RMF systems in terms of retrieval throughput time. An assignment rule based on the handling speeds of workstations is proposed and managed by a neighborhood search algorithm to find a nearly optimal assignment. [He et al. \(2018\)](#) introduce a differentiated probabilistic queuing policy and use an alternating minimization method with simulated annealing to minimize the weighted latency of all customer orders.

Simulation has been used to explore various scenarios to extract general guidelines and results to support decision makers, especially in manufacturing where the problems are complex. Some authors focus on evaluating the impact of several multi-attributes dispatching rules ([Bilge et al., 2006](#); [Guan & Dai, 2009](#); [Singh et al., 2011](#); [Confessore et al., 2013](#); [Zamiri & Choobineh, 2014](#)). These rules can typically include attributes such as travel time or distance to pick up location, input and output buffer size, use of single or multiple-load vehicles, and waiting time. Demand characteristics and constraints from the operating environment have a

significant impact on the responsiveness of AMRs. Simulation has shown to be a powerful tool for multi-scenario analysis that can be integrated with big data analytics and ML techniques.

4.7. Path planning

Problem

Path planning is the task of finding a continuous, deadlock-free path, with little congestion delay for the AMR from the start to the goal position so that it can navigate autonomously between locations, potentially within a large swarm. Compared to AGV routing, which uses a guide path as input, path finding for AMRs uses a representation of the environment to mathematically find the shortest and conflict-free path. An AMR always creates a new, unique path when moving from one point to another. Constraints of static and dynamic obstacles, feasible curvature, robot size, lane dimensions, and speed may be included to find the optimal path with single or combined objectives. In static environments, the path planning is often performed only once, but dynamic environments can require repeating the process of finding a collision-free path multiple times, for multiple vehicles to bypass or to remove the obstacles.

Methods

The methods for path finding can be grouped into those for a single vehicle, for multiple vehicles, and for multiple vehicles with unit load accessibility constraints (i.e. obstacles need to be removed).

Methods for a single vehicle

De Ryck et al. (2020a) explain the graph representations of the environment and graph search algorithms for a single AMR. Their study highlights that the A* and D*Lite algorithms, modifications of Dijkstra's algorithm, are the most popular graph search algorithms to find a shortest path.

Compared to Dijkstra's algorithm which allows to prioritize directions (favoring lower cost paths, e.g. lower costs to encourage moving along straight lines, or higher costs to avoid U-turns) to explore and find the shortest path, the A* algorithm uses a heuristic that prioritizes paths that seem to lead closer to a goal. A* selects the path that minimizes

$$f(n) = g(n) + h(n),$$

where $g(n)$ is the length of the path from the start node to the node n , and $h(n)$ is the heuristic cheapest distance (Manhattan, Euclidean, or Chebyshev) of the current node n to the goal state. Compared to the previous mentioned approaches, the D*Lite algorithm works in the opposite direction which is from the goal to the start and is especially useful to find the shortest path in large and complex areas.

According to Liaqat et al. (2019), simulation is currently not able to properly reproduce the AMR paths and behavior in dynamic environments. In a dynamic environment, many situations occur in which moving obstacles can temporarily block the AMR's path. In their study, experiments support the AMR motion planning reaction to avoid obstacles. They provide protocols that improve the accuracy and quality of path planning simulation in dynamic environments.

Methods for multiple vehicles

In intralogistics systems with multiple vehicles, the shortest path does not necessarily result in the shortest travel time due to constraints such as congestion or deadlock. Several studies use mathematical modeling to introduce conflict-free or deadlock-free strategies to find the shortest path (Wu & Zhou, 2007; Saidi-Mehrabad et al., 2015; Yang et al., 2018), and to solve combinatorial scheduling (Corréa et al., 2007; Ghasezadeh et al., 2009; Nishi et al., 2011), dispatching (Miyamoto et al., 2016), number of vehicles (Vivaldini et al., 2016), and routing problem. The study by

Nishi et al. (2009) applies Lagrangian relaxation to solve the routing problem. It enables the inclusion of various constraints such as loading, unloading, buffering, or coordination with other material handling machines. According to Joseph and Sridharan (2011), routing flexibility has a strong impact on the overall flexibility of a manufacturing system. The study applies simulation and fuzzy logic to analyze the routing flexibility and its effect on efficiency and versatility for a manufacturing system. They provide decision support methods to improve the vehicle routing. The studies by Zhang et al. (2018) and Lyu et al. (2019) apply an improved Dijkstra algorithm to predetermine the initial route of each task. Comparing every route of each vehicle to the given transportation time window, potential congestion can be detected and prevented by suggesting alternative paths. Digani et al. (2019) present an optimization strategy to coordinate a vehicle fleet in automated warehouses to reduce the time mobile robots spend negotiating in complex traffic patterns. A quadratic optimization program, representing a centralized coordination strategy is compared with a decentralized strategy that relies on local negotiations for shared resources. The simulation shows that the coordination strategy can maximize vehicle throughput and minimize the time vehicles spend negotiating traffic under different scenarios. Mohammadi and Shirazi (2020) introduce a tandem-queue-link with a look-ahead approach to enable flexible, collision-free routing in manufacturing systems. Applying simulation, different scenarios are evaluated for congestion, travel time, utilization, and system throughput. Draganjac et al. (2020) propose a decentralized control algorithm that allows each vehicle to plan its own shortest feasible path and to resolve conflict situations with other vehicles by negotiating priority. They use simulation to analyze the intralogistics system for travel distance, system throughput, and energy costs. Franssen et al. (2020) propose a dynamic approach to avoid congestion for large, dense grid-based vehicle systems. Since most approaches in the literature are not rapid enough for real-time control, the introduced method can solve this issue by using a graph representation of the grid system layout with vertex weights that are updated over time. An extensive discrete event simulation allows the proposed path planning approach to significantly increase the throughput and enable recovery from deadlock situations.

Methods for multiple vehicles with obstacle removal

Obstacles (e.g. stored unit loads) can block the AMR paths to fulfill the material handling task. Compared to AGVs, AMRs are not helpless in deadlock situations. For instance, to obtain access to a specific pallet in a truck trailer or to retrieve a unit load in a PBS system, the AMR can move the unit loads that are in front of it or can request support from other AMRs.

For such cases, Gue et al. (2007) investigate the sequencing of movements for retrieving an item from a PBS system with a single 'escort' (i.e. a single open storage space: all other spaces are occupied). Each load has its own vehicle that can lift and move it to a neighboring escort. At each time step, it must be decided which load to move and in which direction. The presented single-escort algorithm finds the optimal path to move an item to the retrieval point, minimizing retrieval time. Alfieri et al. (2012) extend the work of Gue et al. (2007) to systems with multiple empty slots, where multiple vehicles (but fewer than the number of loads) perform the transportation tasks. The proposed heuristic algorithm for conflict avoidance regulates how vehicles should behave in different traffic situations. Mirzaei et al. (2017) extend this to systems where multiple loads must be retrieved and multiple vehicles must be coordinated, with a single escort. They provide an optimal method for two loads and a heuristic method for retrieving more than two loads. Yalcin et al. (2019) propose an exact and heuristic solution algorithm for the single-item retrieval problem in PBS systems with multiple escorts. Their algorithm is based on the A* algorithm and can be used to plan minimum energy movements

for unit loads. The study by [Gue et al. \(2014\)](#) introduces a decentralized control method for PBS systems that follow an Assess-Negotiate-Convey cycle. The heuristic algorithm allows it to assess its current state and the states of its neighbors for each load at each step, and then to move it according to the conveying policy.

In sum, mathematical modeling and simulation modeling have been applied and heuristic algorithms have been proposed to avoid conflicts and deadlocks and to integrate decision variables such as scheduling multiple loads and vehicles. AMRs can find short paths by moving obstacles. However, this capability has hardly been considered in finding the shortest paths, except in PBS systems.

4.8. Robustness and resilience

Problem

A crucial attribute of AMRs is the ability to operate without human surveillance or interference and to recover after failure, guaranteeing a robust and resilient system. Thus, it is necessary to study the internal and external factors that affect system reliability and to introduce decision-making methods that support AMR planning and control abilities.

Methods

The increased navigational flexibility of AMRs can actually lead to increased uncertainty in travel time. [Fazlollahtabar and Olya \(2013\)](#) propose a heuristic statistical technique to compute total stochastic material handling time and develop a cross-entropy approach to model the problem. To ensure system stability, [Tavana et al. \(2014\)](#) introduce an optimization model that uses both time and cost measures to analyze the reliability of a manufacturing system. Bi-objective stochastic programming helps determine optimal reliable production time and cost in a manufacturing system.

Only a few studies have evaluated the ability of AMRs to respond to reliability issues. [Yan et al. \(2017\)](#) apply a failure modes effects and criticality analysis and [Yan et al. \(2018\)](#) propose predictive maintenance strategies for the long-term reliability and stability of the system. To guarantee uninterrupted system performance, [Petrović et al. \(2019\)](#) recommend balancing the utilization and activities of AMRs. Their proposed regulatory measure can increase the AMR life cycle and improve maintenance efficiency.

Dynamic interactions by humans is often neglected in simulation studies. [Fragapane et al. \(2019\)](#) introduce an agent-based simulation model for the use of vehicles in a hospital, using historical material handling data. This facilitates the analysis of the impact of the dynamic environment on performance decline during core business hours and periods of high traffic. Agent-based simulation is especially useful in simulating complex logistics networks and understanding real-world systems with many individual decision making units. The increasing number and density of vehicles in grid-based systems prompted [Fransen et al. \(2020\)](#) to propose a dynamic path planning approach that supports the recovery of AMRs from deadlock situations and increases the robustness of the system.

Widespread acceptance of decentralizing the decision-making process and assigning decisions to AMRs will depend on the overall reliability of the system. Robust systems with stable and predictive results are needed. All AMR risks must be analyzed to discover, refine, and propose methods so that AMRs can achieve reliable performance in various different environments.

5. Research agenda for AMRs

5.1. Approaches and methods used in the planning and control of AMRs

Based on [Section 4](#), we have classified and grouped all 108 reviewed articles on the decision area, prime objectives, methods,

and application area. A detailed description of each reviewed article is provided in [Table 1a](#) (covering [Sections 4.1–4.4](#)) and [Table 1b](#) (covering [Sections 4.5–4.8](#)). Articles discussed and referred to in multiple decision areas are mentioned multiple times. The following paragraphs highlight the insights of the tables for each decision area. An overview and summary of all decision areas can be found at the end of the section ([Table 2](#)).

Decentralized decision-making ([Section 4.1](#)) has received increasing research interest. However, few studies have investigated when decentralized control of material handling is profitable or results in higher performance than centralized control. System throughput and throughput time are the decisive performance measures when analyzing and deciding on the control decentralization level, and thus simulation modeling has so far been the favored method (6/11 papers). Most studies have been conducted in manufacturing rather than in other intralogistics areas (7/11 papers), which might be traced back to the strong promotion of Industry 4.0 to decentralize material handling ([Furmans et al., 2018](#)). Thus, more studies are needed that investigate and compare centralized vs. decentralized control and global vs. local optimization and that analyze different degrees of autonomy in decision-making. Further, more research is needed to investigate how decentralized control affects the profit, resource efficiency, responsiveness, delay, and system robustness and reliability.

Due to the high variety of AMRs (see [Fig. 3](#)), different types of equipment and levels of decentralization are required. Simulation modeling and queuing networks have supported decision-making on determining the number and types of AMRs ([Section 4.2](#)), by analyzing the intralogistics system with system throughput and throughput time as prime objectives, followed by waiting time, utilization and cost. While most studies treat manufacturing and warehousing equally, container terminals have received the highest level of attention in this decision area. Most of the reviewed studies investigate AMRs with lifting or carrying equipment. Methods for analyzing, optimizing, and providing decision-making support for the wide range of equipment and heterogeneous fleets are still lacking.

In the decision area of zoning and service points ([Section 4.3](#)), mathematical modeling has been applied almost exclusively to analyze the intralogistics systems in manufacturing to improve the distribution of workload and to increase the utilization of AMRs. In contrast, queuing networks have mainly been used for warehousing to increase system throughput and decrease travel time, and thus retrieval time. Flexibility in zoning and the location of service points require dynamic approaches. However, only two studies have proposed dynamic approaches. [Ho et al. \(2009\)](#) apply heuristics/meta-heuristics and a simulated annealing approach for load balancing and traffic reduction, and [Azadeh et al. \(2020\)](#) use a closed two-phase server queuing network, embedded in a Markov decision process, to increase throughput capacity. More dynamic methods are needed to adjust quickly to service location fluctuations such as product demand changes in warehousing or treatment demand changes in hospitals. AI algorithms that have rarely been considered in this decision area can facilitate optimization methods to improve the responsiveness, resource consumption, and reliability that are currently lacking. Further, decentralized methods can support AMRs to negotiate zones or request support to handle the demand change when needed.

Only four studies have investigated resource management ([Section 4.4](#)). These studies provide optimization methods and decision support to improve a variety of performance measures in manufacturing and warehousing. The current studies mainly focus on scheduling battery charging and positioning charging stations or inductive charging lines, while the management of the equipment mounted on top of the vehicle has received little attention.

Table 1a
List of 56 reviewed articles for decision areas in Sections 4.1–4.4.

Author	Year	Decision area	Prime objective							Method						Application area				
			Cost/profit	Energy/resource consumption	System throughput	Throughput time/travel distance/makespan	Utilization rate/workload distribution/bottleneck analysis	Work in process/waiting time/congestion and traffic/waste	Responsiveness/tardiness/lateness/delay and penalty cost	Robustness/reliability	Mathematical modelling	Queuing network modeling	Simulation modeling	Optimization methods	Decision science approach (sensitivity/scenario analysis,...)	Manufacturing	Warehousing	Container terminals	Other intralogistics environments	Not specified
Gue <i>et al.</i>	2007	4.1, 4.7			✓	✓							Ex+H/MH	✓		✓				
Maniya <i>et al.</i>	2011	4.1	✓											✓	✓					
Alferi <i>et al.</i>	2012	4.1, 4.7			✓	✓							H/MH		✓	✓		✓		
Gue <i>et al.</i>	2014	4.1, 4.7			✓	✓								✓		✓			✓	
Demesure <i>et al.</i>	2017	4.1				✓										✓				
Wan <i>et al.</i>	2017	4.1	✓	✓												✓				
Zhang <i>et al.</i>	2017	4.1				✓			✓							✓				
Hellmann <i>et al.</i>	2019	4.1	✓				✓							✓		✓				
Kousi <i>et al.</i>	2019	4.1					✓									✓				
Fragapane <i>et al.</i>	2020	4.1			✓											✓				
De Ryck <i>et al.</i>	2020a	4.1, 4.5, 4.7			✓									✓		✓				
<i>Total 11 articles</i>		4.1	3	1	6	6	3	2	0	0	3	0	6	2	6	8	3	0	1	0
Hoshino <i>et al.</i>	2007	4.2	✓										✓	✓					✓	
Fukunari <i>et al.</i>	2008	4.2	✓				✓		✓				✓	✓					✓	
Fukunari <i>et al.</i>	2009	4.2					✓						✓	✓					✓	
Ji <i>et al.</i>	2010	4.2					✓						✓	✓					✓	
Singh <i>et al.</i>	2011	4.2, 4.3, 4.6			✓						✓		✓	✓		✓				
Choobineh <i>et al.</i>	2012	4.2			✓		✓						✓	✓		✓				
Ekren <i>et al.</i>	2010	4.2			✓								✓	✓						
Ekren <i>et al.</i>	2013	4.2			✓								✓	✓						
Ekren <i>et al.</i>	2014	4.2			✓								✓	✓						
Roy <i>et al.</i>	2016	4.2			✓								✓	✓						
Vivaldini <i>et al.</i>	2016	4.2, 4.7				✓							✓	✓					✓	
Zou <i>et al.</i>	2016	4.2	✓		✓								✓	✓						
Gharehgozli <i>et al.</i>	2017	4.2	✓				✓						✓	✓					✓	
Pjavecic <i>et al.</i>	2017	4.2					✓						✓	✓					✓	
Yuan <i>et al.</i>	2017	4.2			✓								✓	✓						
Malopolski	2018	4.2, 4.3				✓							✓	✓		✓				
Ribino <i>et al.</i>	2018	4.2				✓							✓	✓						
Lee <i>et al.</i>	2019	4.2, 4.3				✓							✓	✓						
Lyu <i>et al.</i>	2019	4.2, 4.5, 4.7				✓							Ex GA	✓		✓				
Draganjac <i>et al.</i>	2020	4.2, 4.7	✓	✓									✓	✓		✓				
Roy <i>et al.</i>	2020	4.2			✓								✓	✓					✓	
Wang <i>et al.</i>	2020	4.2			✓								✓	✓						
Zhang <i>et al.</i>	2020	4.2			✓								✓	✓						
<i>Total 23 articles</i>		4.2	5	1	12	10	7	8	3	0	7	13	17	2	8	7	12	5	1	0
Shalaby <i>et al.</i>	2006	4.3	✓										✓	H/MH		✓				
Asef-Vaziri <i>et al.</i>	2007	4.3			✓								✓	Ex+H/MH		✓				
Farahani <i>et al.</i>	2007	4.3				✓							✓	GA		✓				
ElMekkawy <i>et al.</i>	2009	4.3					✓						✓	MA		✓				
Ho <i>et al.</i>	2009	4.3					✓						✓	H/MH+SA		✓				
Singh <i>et al.</i>	2011	4.2, 4.3, 4.6			✓								✓			✓				
Roy <i>et al.</i>	2012	4.3			✓								✓			✓				
Hamzeei <i>et al.</i>	2013	4.3					✓						✓	Ex+SA		✓				
Tubailieh	2014	4.3					✓						✓	SA		✓				
Lamballais <i>et al.</i>	2017	4.3			✓								✓			✓				
Asef-Vaziri <i>et al.</i>	2018	4.3					✓						✓	EA		✓				
Malopolski	2018	4.2, 4.3				✓							✓			✓				
Qi <i>et al.</i>	2018	4.3				✓							✓			✓				
Azadeh <i>et al.</i>	2019b	4.3			✓								✓			✓				
Lee <i>et al.</i>	2019	4.2, 4.3				✓							✓	Ex		✓				
Roy <i>et al.</i>	2019	4.3			✓								✓			✓				
Azadeh <i>et al.</i>	2020	4.3			✓								✓			✓				
Lamballais <i>et al.</i>	2020	4.3			✓								✓			✓				
<i>Total 18 articles</i>		4.3	1	0	8	7	9	4	1	0	10	6	8	9	6	10	8	0	0	0
Boysen <i>et al.</i>	2018	4.4												GA						✓
Zou <i>et al.</i>	2018b	4.4	✓		✓								✓			✓				
Kabir <i>et al.</i>	2019	4.4				✓							✓			✓				
De Ryck <i>et al.</i>	2020b	4.4		✓									✓	H/MH+PSO		✓				
<i>Total 4 articles</i>		4.4	1	1	1	1	2	0	1	0	2	1	1	2	1	2	1	0	0	1

AC: Ant Colony Approach, AT: Auction Theory, EA: Evolutionary Algorithm, Ex: Exact Optimization, GA: Genetic Algorithm, H/MH: Heuristics/Meta-Heuristics, MA: Memetic Algorithm, PSO: Particle Swarm Optimization, SA: Simulated Annealing, SFHA: Sheep Flock Heredity Algorithm, WA: Whale Optimization Algorithm.

Table 1b
List of 74 reviewed articles for decision areas in Sections 4.5–4.8.

Author	Year	Decision area	Prime objective		Method										Application area					
			Cost/profit	Energy/resource consumption	System throughput	Throughput time/travel time/travel distance/makespan	Utilization rate/workload distribution/bottleneck analysis	Work in process/waiting time/congestion and traffic/waste	Responsiveness/tardiness/lateness/delay and penalty cost	Robustness/reliability	Mathematical modelling	Queuing network modeling	Simulation modeling	Optimization methods	Decision science approach (sensitivity/scenario analysis,...)	Manufacturing	Warehousing	Container terminals	Other intralogistics environments	Not specified
Ho et al.	2006	4.5			✓							✓		✓						
Jerald et al.	2006	4.5					✓	✓		✓			GA	✓						
Corréa et al.	2007	4.5, 4.7					✓	✓		✓			H/MH	✓						
Deroussi et al.	2008	4.5				✓		✓		✓			H/MH+SA	✓						
Ghasemzadeh et al.	2009	4.5, 4.7					✓	✓		✓			H/MH	✓						
Udhayakumar et al.	2010	4.5				✓		✓		✓			GA+AC	✓						
Nishi et al.	2011	4.5, 4.7						✓		✓			H/MH	✓						
Rashidi et al.	2011	4.5				✓		✓		✓			Ex+H/MH			✓				
Anandaraman et al.	2012	4.5				✓		✓		✓			SFHA	✓						
Lacomme et al.	2013	4.5					✓			✓			MA	✓						
Zheng et al.	2014	4.5					✓			✓			H/MH	✓						
Fazlollahabbar et al.	2015	4.5						✓		✓			H/MH	✓						
Saïdi-Mehrabad et al.	2015	4.5, 4.7				✓				✓			AC	✓						
Baruwa	2016	4.5					✓				✓		H/MH	✓						
Fazlollahabbar	2016	4.5					✓			✓			H/MH	✓						
Gen et al.	2017	4.5, 4.6						✓		✓			GA	✓						
Mousavi et al.	2017	4.5					✓			✓			GA+PSO	✓						
Fazlollahabbar et al.	2018	4.5	✓				✓			✓			Ex	✓						
Yang et al.	2018	4.5, 4.7					✓			✓			GA						✓	
Zeng et al.	2018	4.5					✓			✓			AT			✓				
Bakshi et al.	2019	4.5					✓			✓			H/MH	✓						
Bocewicz	2019	4.5			✓			✓		✓			Ex	✓						
Lei et al.	2019	4.5					✓			✓			MA	✓						
Lyu et al.	2019	4.2, 4.5, 4.7					✓			✓			GA	✓						
Petrović et al.	2019	4.5, 4.8					✓			✓			WA	✓						
Chen	2020	4.5								✓			GA	✓						✓
De Ryck et al.	2020a	4.1, 4.5, 4.7					✓			✓				✓						
Polten et al.	2020	4.5						✓		✓			H/MH	✓						✓
Rahman et al.	2020	4.5						✓		✓			H/MH+PSO	✓						✓
Total 29 articles		4.5	1	0	5	16	4	8	14	0	26	0	3	27	3	25	1	3	0	0
Bilge et al.	2006	4.6				✓			✓					✓						
Lin et al.	2006	4.6					✓						GA	✓						
Guan et al.	2009	4.6				✓		✓						✓						
Ventura et al.	2009	4.6						✓					H/MH	✓						
Singh et al.	2011	4.2, 4.3, 4.6				✓				✓				✓						
Confessore et al.	2013	4.6					✓							✓						
Zamiri et al.	2014	4.6					✓							✓						
Smith	2015	4.6					✓				✓			✓						
Umar et al.	2015	4.6						✓					GA	✓						
Ventura et al.	2015	4.6						✓					GA	✓						
Miyamoto et al.	2016	4.6, 4.7						✓					H/MH	✓						
Gen et al.	2017	4.5, 4.6						✓					GA	✓						
Zou et al.	2017	4.6						✓				✓		✓						✓
Bozer et al.	2018	4.6						✓						✓						
He et al.	2018	4.6						✓				✓		H/MH+SA	✓					✓
Total 15 articles		4.6	0	0	3	8	5	2	8	0	7	3	8	7	8	13	2	0	0	0

(continued on next page)

Table 1b (continued)

Author	Year	Decision area	Prime objective			Method										Application area				
			Cost/profit	Energy/resource consumption	System throughput	Throughput time/travel time/travel distance /makespan	Utilization rate /workload distribution /bottleneck analysis	Work in process /waiting time /congestion and traffic /waste	Responsiveness-tardiness /lateness /delay and penalty cost	Robustness /reliability	Mathematical modelling	Queuing network modeling	Simulation modeling	Optimization methods	Decision science approach (sensitivity /scenario analysis,...)	Manufacturing	Warehousing	Container terminals	Other intralogistics environments	Not specified
Corréa et al.	2007	4.5, 4.7						✓	✓	✓				H/MH		✓				
Gue et al.	2007	4.1, 4.7			✓	✓				✓				Ex + H/MH	✓		✓			
Wu et al.	2007	4.7				✓				✓				H/MH		✓				
Ghasemzadeh et al.	2009	4.5, 4.7						✓	✓	✓				H/MH		✓				
Nishi et al.	2009	4.7	✓							✓				H/MH						✓
Nishi et al.	2011	4.5, 4.7							✓	✓				H/MH		✓				
Joseph et al.	2011	4.7					✓	✓		✓										
Alfieri et al.	2012	4.1, 4.7			✓	✓				✓		✓		H/MH			✓			✓
Gue et al.	2013	4.1, 4.7			✓	✓				✓		✓			✓		✓			
Saidi-Mehrabad et al.	2015	4.5, 4.7				✓				✓				AC		✓				
Miyamoto et al.	2016	4.6, 4.7							✓	✓				H/MH		✓				
Vivaldini et al.	2016	4.2, 4.7								✓		✓					✓			
Mirzaei et al.	2017	4.7			✓	✓				✓		✓		Ex + H/MH			✓			
Yang et al.	2018	4.5, 4.7				✓				✓				GA				✓		
Zhang et al.	2018	4.7						✓		✓		✓		H/MH	✓			✓		
Digani et al.	2019	4.7				✓				✓		✓					✓			
Liaquat et al.	2019	4.7				✓				✓		✓					✓			
Lyu et al.	2019	4.2, 4.5, 4.7				✓			✓	✓		✓		GA		✓				
Yalcin et al.	2019	4.7			✓	✓				✓		✓		Ex + H/MH			✓			
De Ryck et al.	2020a	4.1, 4.5, 4.7			✓	✓				✓		✓			✓		✓			
Draganjac et al.	2020	4.2, 4.7	✓	✓	✓					✓		✓			✓		✓			
Fransen et al.	2020	4.7, 4.8				✓		✓		✓		✓								✓
Mohammadi et al.	2020	4.7				✓	✓	✓		✓		✓		H/MH		✓				✓
Total 23 articles		4.7	2	1	7	16	2	9	5	1	15	0	12	15	5	11	9	1	2	1
Fazlollahtabar et al.	2013	4.8				✓				✓		✓		H/MH		✓				
Tavana et al.	2014	4.8	✓			✓				✓		✓		Ex		✓				
Yan et al.	2017	4.8								✓		✓			✓					✓
Yan et al.	2018	4.8								✓		✓			✓					✓
Fragapane et al.	2019	4.8				✓	✓	✓		✓		✓								✓
Petrović et al.	2019	4.5, 4.8				✓	✓	✓		✓		✓		WA		✓				
Fransen et al.	2020	4.7, 4.8				✓		✓		✓		✓								✓
Total 7 articles		4.8	1	0	0	5	2	3	0	6	3	0	4	3	2	3	0	0	2	2

AC: Ant Colony Approach, AT: Auction Theory, EA: Evolutionary Algorithm, Ex: Exact Optimization, GA: Genetic Algorithm, H/MH: Heuristics/Meta-Heuristics, MA: Memetic Algorithm, PSO: Particle Swarm Optimization, SA: Simulated Annealing, SFHA: Sheep Flock Heredity Algorithm, WA: Whale Optimization Algorithm.

Table 2
Number of papers per decision area, prime objectives, methods used in the decision-making process, and application areas.

Decision area	Articles	Prime objective								Method					Application area				
		Cost/profit	Energy /resource consumption	System throughput	Throughput time/travel time/travel distance/makespan	Utilization rate/workload distribution/bottleneck analysis	Work in process/waiting time/congestion and traffic/waste	Responsiveness /tardiness/lateness/delay and penalty cost	Robustness/reliability	Mathematical modelling	Queuing network modeling	Simulation modeling	Optimization methods	Decision science approach (sensitivity/scenario analysis,...)	Manufacturing	Warehousing	Container terminals	Other intralogistics environments	Not specified
4.1 Control decentralization level	11	3	1	6	6	3	2	0	0	3	0	6	2	6	8	3	0	1	0
4.2 Number and type of vehicles	23	5	1	12	10	7	8	3	0	7	13	17	2	8	7	12	5	1	0
4.3 Zoning and service points	18	1	0	8	7	9	4	1	0	10	6	8	9	6	10	8	0	0	0
4.4 Resource management	4	1	1	1	1	2	0	1	0	2	1	1	2	1	2	1	0	0	1
4.5 Scheduling	29	1	0	5	16	4	8	14	0	26	0	3	27	3	25	1	3	0	0
4.6 Dispatching	15	0	0	3	8	5	2	8	0	7	3	8	7	8	13	2	0	0	0
4.7 Path planning	23	2	1	7	16	2	9	5	1	15	0	12	15	5	11	9	1	2	1
4.8 Robustness and resilience	7	1	0	0	5	2	3	0	6	3	0	4	3	2	3	0	0	2	2
<i>Total</i>	<i>130</i>	<i>14</i>	<i>4</i>	<i>42</i>	<i>69</i>	<i>34</i>	<i>36</i>	<i>32</i>	<i>7</i>	<i>73</i>	<i>23</i>	<i>59</i>	<i>67</i>	<i>39</i>	<i>79</i>	<i>36</i>	<i>9</i>	<i>6</i>	<i>4</i>

*Articles included in several decision areas appear multiple times.

Future studies will have to provide decision support for positioning the storage of sharing equipment and multi-objective optimization methods for scheduling the sharing of equipment among a fleet. Optimization methods for battery and equipment could increase AMR availability, thus reducing costs and increasing productivity.

Scheduling vehicles and loads (Section 4.5) has received the most attention in literature, with 29 articles. Most applications can be found in manufacturing (25/29 papers), with a focus on makespan and delay optimization. Mathematical modeling and a wide variety of optimization techniques have been introduced and investigated (26/29 papers). Compared to other decision areas, AI-based techniques methods such as evolutionary algorithms, genetic algorithms, memetic algorithms and, furthermore, swarm intelligence-based methods such as the ant colony approach, particle swarm optimization, sheep flock heredity algorithms, and the whale optimization algorithm have been widely applied. In comparison to scheduling, dispatching (Section 4.6) has focused more on queuing network and simulation modeling to improve the main objectives of makespan and responsiveness. Scheduling is used in container terminals, while dispatching methods are more commonly used in warehousing. However, optimization methods for scheduling and dispatching focused on resource consumption and reliability are still lacking. Optimization methods for scheduling and dispatching in other intralogistics systems are also lacking.

The decision area of path planning (Section 4.7) has received increasing interest in recent years. While there has been a greater focus on reducing traffic, congestion and conflict, more recent studies highlight the potential of finding paths by moving unit loads that are blocking the shortest path. Mathematical modeling and simulation have supported analyses of warehousing and manufacturing and introduced heuristics improving the overall objectives of travel distance, travel time, traffic, and system throughput. While path planning with obstacle removal has been investigated in especially compact warehouses, studies for manufacturing and other intralogistics systems are still lacking. The increased level of decentralized control and flexibility in path planning and equipment require methods to establish robust and resilient systems (Section 4.8). However, few studies have provided methods aiming at stable and reliable systems. The reviewed studies have applied mathematical modeling and simulation to optimize robustness, reliability, and throughput time. New methods are needed to support autonomous material handling systems to react appropriately in case of failures and to work independently without human surveillance. These methods would enable proactive work environments that can reduce failures and reboot autonomously instead of requiring a cold restart in times of failure.

Overall, the prime objectives have been throughput time, travel time, travel distance, and makespan minimization and system throughput and utilization maximization (see Table 2). Mathematical modeling is the most frequently applied method for long-term decisions in decision support and for short-term decisions for optimization purposes. Queuing modeling has been found to be useful in modeling warehousing and container terminals, and simulation modeling has found great interest and applicability in overall intralogistics systems. Few articles focus on decision-making at the strategic level (control decentralization level, Section 4.1). Instead, most of the reviewed articles focus on decision-making at the tactical-operational level. Scheduling is the most strongly represented method (22% of all reviewed articles), followed by path planning (18%), determining the number and types of vehicles (18%), zoning and service points (14%), dispatching (12%), control decentralization (8%), robustness and resilience (5%), and resource management (3%).

Several studies see strong potential to improve performance yields by addressing multiple decision variables simultaneously, such as determining the number of vehicles, determining zoning

and service point locations (Singh et al., 2011; Małopolski, 2018), or simultaneous scheduling and path planning (Corréa et al., 2007; Ghazemzadeh et al., 2009; Nishi et al., 2011; Petrović et al., 2019). This allows us to understand how the different decisions interact and to evaluate them to make more balanced decisions. For instance, research on the number and types of vehicles and resource management can support reduced costs and increased utilization by analyzing how to share the equipment mounted on top of the vehicle. This influences the number of required vehicles. Moreover, dispatching, path planning, and robustness and resilience can help to increase the uptime of an intralogistics system. Analyzing these decision areas simultaneously makes it possible to investigate how swarm behavior can be used to dispatch and navigate other AMRs in case of an AMR breakdown and thus guarantee a robust and resilient intralogistics system. Further, the decision areas of zoning and scheduling or zoning and dispatching should be investigated simultaneously. In current studies, the output of one decision area is the input data for the other. Optimizing these decision areas simultaneously would result in a larger variety of possibilities and enable the identification and achievement of a new optimum. AI techniques can support to solve multi-objective optimization (Petrović et al., 2019) and are especially useful for integrating decision areas, such as zoning and dispatching, with objectives related to cost, resource consumption, responsiveness, system throughput, and travel time.

Manufacturing and warehousing applications have dominated the research on AMRs in intralogistics. Other intralogistics applications have received little attention (Table 2). However, the use of AMRs in other intralogistics areas is growing rapidly, offering opportunities for modelling and optimization.

In hospitals and nursing homes, AMRs can fill the gap in transporting critical, on-demand materials through narrow hallways, high traffic areas and dynamic environments. Agent-based simulations can support modeling different traffic scenarios with human interaction and analyze different path planning approaches to increase safety, quality, and transportation performance. Further, semi-open queuing network modeling can support determining the number of vehicles, while minimizing customer waiting times and improving the utilization and cost performance of AMRs mounted with hospital equipment shared among departments.

In agriculture, for handling delicate materials, AMRs with sensing and picking equipment can benefit from methods developed for warehouses with pick-and-fetch robots. Picking fruits or flowers is challenging since they are prone to damage during the harvesting process. As the AI branches of vision and ML evolve, sensing and picking delicate materials is becoming more feasible. The uncertainty in forecasting the harvest time period is a challenge for labour planning. Quickly upscaling an AMR fleet when needed can increase quality and productivity in agriculture, and reduce food waste.

In restaurants, automated delivery of dishes is not new (e.g. conveyors in sushi bars). However, unidirectional conveyors that do not stop allow for less flexibility in terms of layout and transportation variety. AMRs enable free navigation and on-demand transportation from the kitchen to the customer and vice versa. The rich knowledge of modeling in manufacturing can help decrease manual transportation and human fatigue in restaurants, and support rapid adjustment to customer arrival rates and volumes by increasing or decreasing the AMR fleet.

5.2. Research agenda

Based on the analyses in the previous sections, we can draw conclusions on the future research agenda for planning and control of AMRs. The objective should be to operate a cost-efficient,

flexible, scalable, proactive, and robust system. The future research agenda should include the following:

- More studies are needed in assisting and deciding which operations should be centralized and decentralized and what degree of autonomy should be given to the AMR, and under which circumstances performance benefits. Multi-scenario analyses and agent-based simulations are promising methods that can help refine the decision-making process, especially in new AMR application areas. Agent-based simulation makes use of self-regulating, self-governing resource units that follow a series of predefined rules to achieve their objectives whilst interacting with each other and their environment system. This method allows integrating different levels of decentralization.
- New approaches are needed to evaluate the number of vehicles, since AMRs are entering new intralogistics environments and provide more services. Methods are needed that include the uncertainties of a dynamic environment like traffic, varying travel paths and distances, variable service points within a zone and different service activities, to determine the optimal number of vehicles. Moreover, methods are needed to find the optimal ratio of different types of AMRs within a fleet. Simulation modeling in combination with big data, machine learning, and predictive analytics can support this. Also, queuing, flow, and traffic theory can assist in analyzing overall obstacle avoidance as a factor in assessing performance improvement or degradation.
- New decision models for the management of AMR equipment are needed. AMR equipment will play a crucial role in integrated scheduling of manufacturing and warehousing operations, but also in new application areas. Think of models where vehicles with different equipment collaborate, or where equipment or tools can be swapped to carry out specific tasks. New methods are needed to support decision-making on how to plan and optimally share equipment in intralogistics systems.
- AMRs can be integrated rapidly into new environments. This, however, calls for efficient and fast methods for designing work zones and finding handover point positions. Work zones can also become dynamic, as they are mainly software embedded, and the number and size of zones can rapidly be adapted to the workload or work composition. New methods are needed to distribute AMRs within zones to ensure high response and performance. Big data and predictive analytics can help identify where AMRs should idle while awaiting their next request. AMRs can further share demand patterns and negotiate with each other for smart, decentralized distribution.
- Large-scale AMR systems (e.g. Amazon warehouses with thousands of interacting AMRs) will inevitably rely on decentralized scheduling. Therefore, new methods and approaches besides auction-based task allocation should be proposed. New optimization models for both large-scale systems and multi-objective optimization are needed. AI-based algorithms for multi-objective optimization can offer support to such investigations.
- Methods inspired by nature such as swarm optimization, ant colony optimization, and firefly algorithms can inject intelligence into path planning. New simulation methods are needed to integrate AMR behavior in dynamic environments. Furthermore, methods for path planning with unit load accessibility constraints should be investigated in manufacturing and other intralogistics systems.
- Finally, more research on system robustness and reliability is needed. New simulation models may support the autonomous decision-making processes when AMRs fail. AI techniques such as ML can support AMRs to react dynamically and independently without human surveillance in case of failures. New

predictive methods for e.g. maintenance will support AMRs to work proactively to reduce the number failures.

6. Conclusion

The technological advances of AMRs have significantly helped to achieve operational flexibility and to increase performance in productivity, quality and (sometimes) cost efficiency. Taking decisions autonomously thanks to AI promotes the decentralization of activities involving AMRs. The systems can often be implemented rapidly, particularly in those application areas where suppliers have developed expertise in past implementation projects. However, it is still difficult to estimate the benefits that AMRs will bring and to determine how they should be deployed to reap maximum benefits. This literature study has detailed the crucial technological developments and identified decision areas for the planning and control of AMRs. We have structured and analyzed the literature, have given a definition of AMRs, and have proposed a planning and control framework. Based on the literature, decision areas with applied objectives and approaches have been identified. In summary, most studies in this field have focused on manufacturing and warehousing, and thus, research on many other intralogistics application areas is still lacking. Only a few studies have investigated the conditions under which decentralized control is more profitable compared to centralized control, or results in higher performance. Addressing multiple decision variables simultaneously, such as determining the number of vehicles, determining zoning and service point locations or simultaneous scheduling and path planning, improves the understanding of how different decisions interact and allows their evaluation to provide more balanced decisions. AI techniques are especially useful for integrating decision areas since they can support solving multiple objectives. We conclude that, although research is growing rapidly, several research areas have still received little attention, leading to a future research agenda.

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