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

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Abstract

Many intralogistics businesses, including manufacturing, warehouses, cross-docks, terminals, and hospitals, are presently using autonomous mobile robots (AMR). They can operate independently in dynamic conditions because to their sophisticated hardware and control software. AMRs can interact and bargain with other resources, such as machines and systems, independently, which decentralizes the decision-making process in contrast to an automated guided vehicle (AGV) system, where a central unit controls scheduling, routing, and dispatching decisions for all AGVs. The system may respond dynamically to changes in the environment and system status thanks to decentralized decision-making. The conventional approaches and decision-making procedures for planning and control have been impacted by these advances. Research on the design and management of AMRs in intralogistics is identified and categorized in this study. We provide a comprehensive literature analysis that emphasizes the impact of AMR technology advancements on planning and control choices. In order to help managers make the best decisions and attain optimum performance, we add to the literature by presenting an AMR planning and control framework. Lastly, we provide a research plan for this area of study.

Introduction

Rapid advancements in materials handling technologies have been made in recent decades. The transformation of automated guided vehicles (AGV) into autonomous mobile robots (AMR) is one significant advancement. Since the introduction of the first AGV in 1955 (Muller, 1983), the guiding system, which is the fundamental component of AGV material handling systems, has undergone many phases of development, including mechanical, optical, inductive, inertial, and laser guidance, culminating in the current vision-based system (Fig. 1). By utilizing ubiquitous sensors, potent on-board computers, artificial intelligence (AI), and simultaneous location and mapping (SLAM) technology, this vision-based system allows the device to comprehend its operating environment and navigate within buildings without requiring reference points to be pre-defined and put into place. This has increased navigational freedom to a new level. Only fixed pathways and predetermined places on the guiding path may be traversed by conventional AGVs (Fig. 1(a)–((f)). AMRs, on the other hand, may go to any available, collision-free location inside). a specific region (Fig. 1(g)). For most AGV guidance systems, minor adjustments like changing the machine configuration, for instance, would take a long time, result in periods of inactivity, and run the risk of economic losses and productivity declines. On the other hand, AMRs are able to swiftly adjust to changes in the operational environment. The development of AMRs has been fueled by the demand for more flexibility, both in terms of their navigational capabilities and the services they can provide. AMRs can perform a wide range of tasks beyond simple transport and material handling, including patrolling and operator collaboration, in contrast to AGVs, which are defined as computer-controlled, wheel-based load carriers for horizontal transportation without the need for an onboard operator or driver (Le-Anh & De Koster, 2006). These mobile platforms may provide adaptable solutions when paired with the capacity for independent decision-making. Because AMR cars are autonomous, they must constantly make decisions about how to operate in a setting that complies with laws and regulations. The total lack of a human supervisor who is aware of the limitations of the system is a significant difficulty. Therefore, an AMR has to be able to independently monitor its own condition, identify any system flaws, and respond accordingly. Advanced capabilities for autonomous operation are made possible by the AMR's hardware and control software, not just

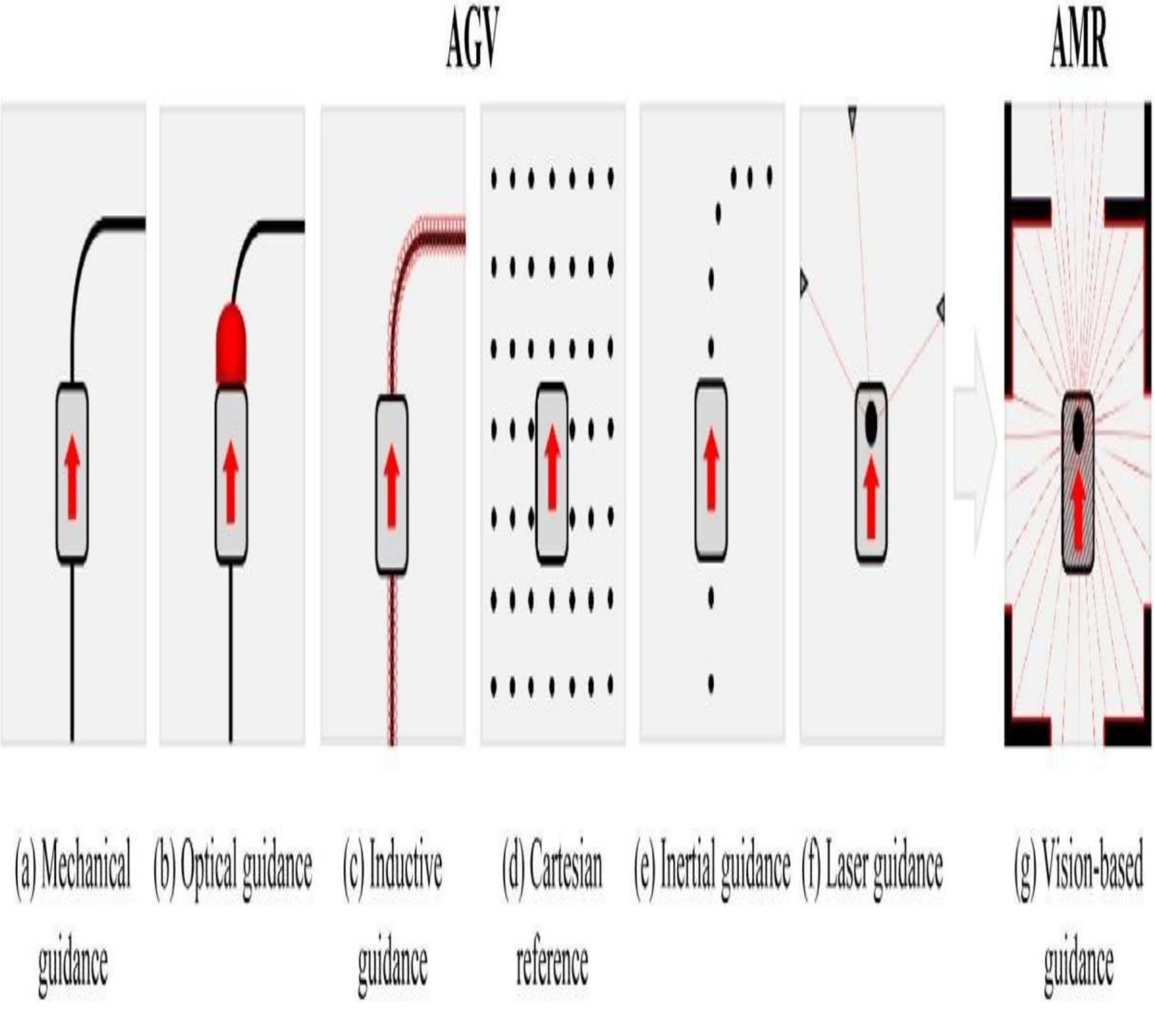
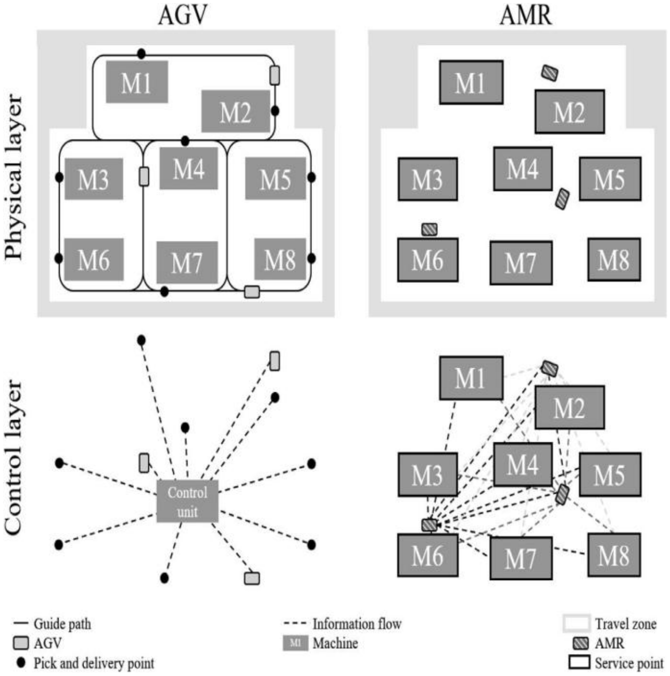


Fig. 1. Guiding systems for AGVs and AMRs (top view of the system).

object manipulation as well as object detection in dynamic and unstructured settings (Hernández et al., 2018). Decision-making processes have become more decentralized as a result of these developments. AMRs can interact and negotiate with other resources, including machines and systems like enterprise resource planning or material handling assessment and control software (Fig. 2), independently, and make decisions on their own, unlike AGV systems where a central unit makes decisions about routing and dispatching for all AGVs. As a result, less external, centralized control is required (Furmans & Gue, 2018). The AMR decentralized decision-making process aims to enable each vehicle to continually optimize itself while responding dynamically to demand or changes.

The idea of AMR is not new. 1987 saw the issuance of the first generic AMR patent (Mattaboni, 1987). Since then, it has mostly been explored in the domains of information technology and robotics, but it has lately surfaced in logistics applications, and its significance is anticipated to grow considerably in the near future. According to estimates, there are really over 13,000 AGV and AMR systems deployed worldwide (Bechtsis et al., 2017). Autonomous robots are now available from hundreds of providers globally. Basic cars may be put together at a reasonable cost by using generic parts, including as sensors, batteries, driving and steering systems, manipulating equipment, and processing devices. Manufacturing systems, warehouses, and container terminals have historically been the primary industries with AGV applications (Le-Anh et al., 2006). However, their service offerings and areas of application have expanded dramatically. AMRs today perform a variety of activities in industrial, hospital, hotel, security, and residential environments.



AMRs may be utilized as helpful systems in addition to loading and transporting machines since they can communicate with people as colleagues (Fig. 3(c)). AMRs with manipulators may help workers in the automotive industry by mounting heavy vehicle body pieces at various points along the assembly line (Angerer et al., 2012). This increases quality and productivity while also lowering worker fatigue.

AMRs and operators work together to select orders in warehouses (Fig. 3(p)). Inside the picking regions, AMRs transport a few little containers before coming to a halt in front of the spot where the operator has to choose the subsequent item. After that, they alone go to the next destination. The AMR automatically moves to the packing and consolidation section after collecting every item in a particular order. There, it is emptied and delivered to a fresh batch of orders (Meller et al., 2018; Azadeh et al., 2019a). A zone-picking approach that maximizes operator and AMR picking and traveling efficiency is made possible by this technology. In high-traffic, narrow-aisle settings, such as warehouses and hospitals, the potency of AMRs is particularly evident. AGVs do

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

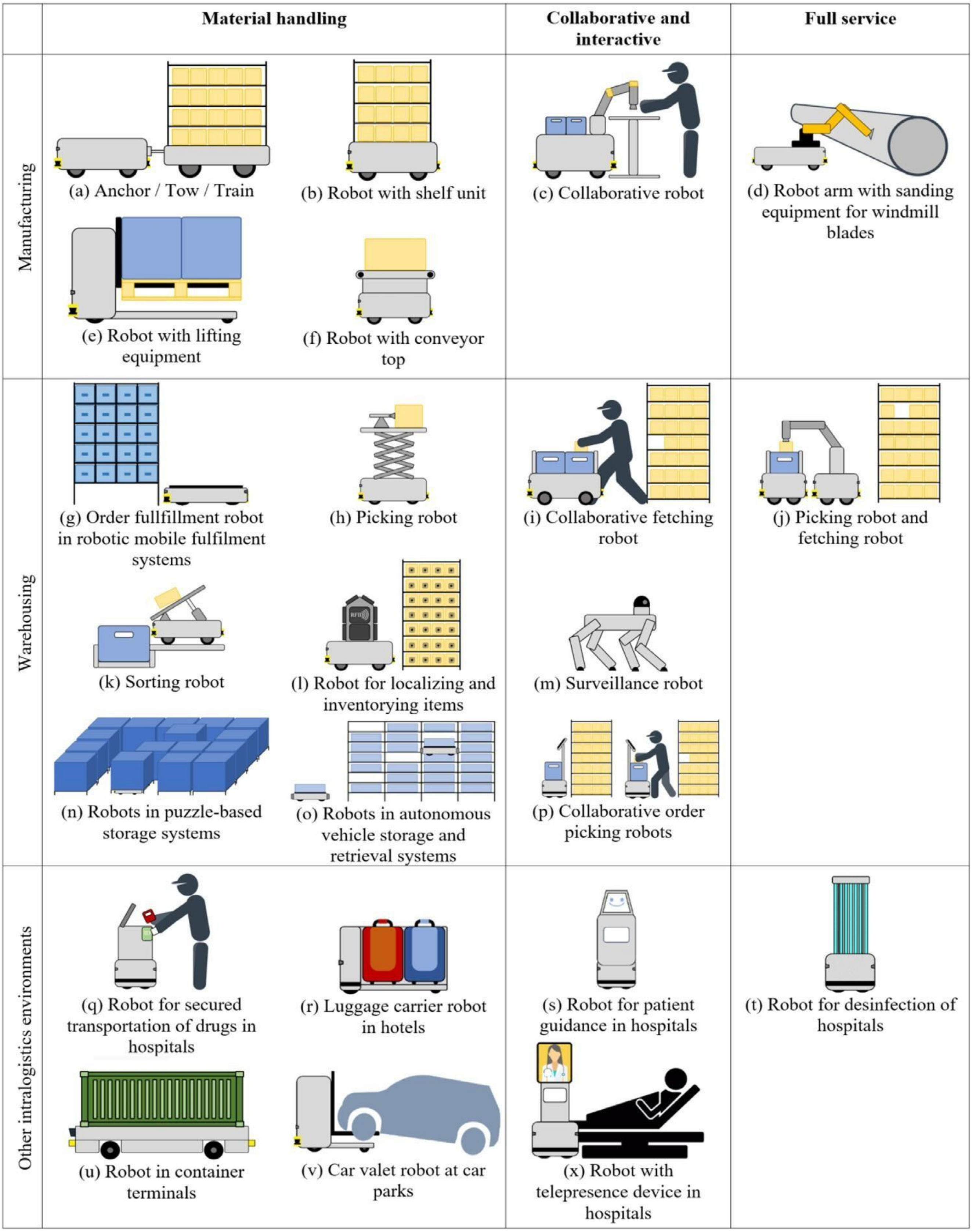


Fig. 3. Types of AMRs and examples of applications.

to almost every department and may be used for urgent and timely delivery, such as cancer medications or radioactive therapeutic and diagnostic medications whose proper dosage quickly decays (Fig. 3(q)). Apart from transportation duties, they may provide services like telemedicine, room disinfection, or guide assistance (Fig. 3(s, t, x)) (Fragapane et al., 2020a). AMRs may significantly cut down on manual material handling in hospitals, freeing up more time for patient-related tasks and giving direct-care employees more valuable time. The tasks completed define and categorize AMRs into three primary categories. Material handling (retrieval, movement, transportation, sorting, etc.) is one of their services (Fig. 3). Other services include (II) interactive and cooperative activities and (III) full-service activities. According to Hernández et al. (2018) and Indri et al. (2019), they have the following qualities: Using intelligent, cognitive, and behavior-based control techniques and technologies to maximizeflexibility and roductivity performance is known as decentralized control. • Platform operation: offering a means of expanding an AMR's potential applications and capabilities beyond standard material handling tasks. • Collaborative operation: collaborating with other AMRs in a swarm or with humans. • Simplicity of integration: incorporating quick and affordable AMRs into a manufacturing plant or other establishment. • Scalability: the capacity to increase or decrease the number of AMRs without structural change impeding the process. • Robustness: offering resilience, or systems that can bounce back from setbacks. In conclusion, the authors of this research suggest and use the following definition: Autonomous mobile robots are industrial robots that provide a platform for material handling, teamwork, and complete services inside a defined region by using a decentralized decision-making method for collision-free navigation.

A new decision-making framework is necessary due to AMRs' growing capacity to take over jobs and activities as well as the fact that they move, function, and interact with people and equipment differently than AGVs. For managers to function at their best, they need direction while making decisions. Determining the extent of control decentralization of assistive material handling tasks for AMRs in automobile manufacturing, for example, is crucial at the strategic decision level. Work zones for cooperative AMRs in warehouses need to be established at the tactical level. Hospitals must design safe, low-contagious-risk AMR travel routes at the operational level.

The majority of the literature on AMRs is technological in nature and is dispersed. Another factor impeding study in this area is the absence of a single, widely recognized definition among practitioners and scholars. The majority of the research on vehicle planning and control systems has focused on AGVs. While Bechtsis et al. (2017) provide a literature review concentrating on sustainability factors in AGV planning and control, Vis (2006) and Le-Anh et al. (2006) identify important decision areas, such as guide route design and deciding on the quantity and locations of pick-up and delivery stations. Many diverse choices at the strategic, tactical, and operational levels must be made as a consequence of the increased degree of autonomy, applicability, and flexibility that AMRs give, and this number keeps rising. However, AMRs have not received enough scholarly attention because of the limited number of applications they currently have. It is important to study the existing AGV planning and control techniques and determine if they can be expanded, transferred, or changed for AMRs. The current study identifies and categorizes studies pertaining to the planning and management of AMRs, starting with the literature on AGVs, and suggests a research agenda for the future. The primary components of mobility (i.e., unrestricted navigation), autonomy (i.e., decision-making), and robotics (i.e., service provision) are the emphasis. The following research questions are examined:

- What impact do AMRs' technical advancements have on choices about planning and control?
- Which strategies and techniques are most prevalent in the literature on AMR planning and control?
- What more studies are required for AMR planning and control?

We conducted a literature review that includes English-language materials from online databases such as ScienceDirect, Web of Science, and Google Scholar in order to address these topics. The terms "Automated Guided Vehicle," "Autonomous Intelligent Vehicle,""Autonomous Mobile Robot," "Mobile Robotic Fulfillment," "Collaborative Mobile Robot," "Mobile Service Robot," and "Puzzle Based Storage System" were used, along with their variations. After that, we focused our search. First, we limited our search to papers released during the last 15 years. Two literature studies by Le-Anh et al. (2006) and Vis (2006), which outline the primary techniques and approaches prior to 2006, have sufficiently addressed older material on AGVs. Second, as we believe that significant research has ultimately been published in peer-reviewed academic publications, we did not include conference proceedings, professional journals, book chapters, or doctorate dissertations. Third, only publications published in journals with a Scimago Journal

Rank greater than 0.5 were considered, and we concentrated on high-impact journals. The titles and abstracts of the 302 surviving papers were then thoroughly vetted. Included were only full-text English-language studies that dealt with AMRs or AGVs (if applicable and relevant to AMRs). To ensure their applicability to AMR planning and control, the remaining papers were all full-text checked in the last stage. Upon reviewing the reference lists, a few very pertinent publications that have been mentioned several times but have not been previously recognized have also been added. The final review had 108 papers in total.

This is how the remainder of the paper is structured. AMRs' significant technical advancements are presented in Section 2, along with an explanation of how they have impacted AGV decision-making. We provide a paradigm for AMR decision-making in Section 3, outlining the primary distinctions from AGV choices. The planning and control choices, as well as the operational research techniques used, are explained in Section 4. Section 5 presents detailed suggestions for future study topics and quantifies and summarizes current ways to detect gaps in the literature. In Section 6, we wrap up.

1. 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.

1.1 *Hardware*

1.1.1 *Sensors*

2. AMRs usually include a variety of tiny, inexpensive, and power-efficient sensing devices that provide information for self-navigating vehicles. These integrated laser scanners, which include Light Detection and Ranging (LiDAR), 3D cameras, accelerometers, gyroscopes, and wheel encoders, capture and transmit vast amounts of data about the AMR's immediate, extended, and anticipated environments as well as its internal condition. They also provide information on wheel positions to calculate the distance that the robot has driven or turned (De Silva et al., 2018). 3D cameras provide wide-angle assistance that makes it possible to visually identify obstacles, while LiDAR laser scanners offer a very accurate distance point cloud in relation to the AMR and its surroundings. Because of their rapid result rendering and ease of dynamic use, these technologies have gained popularity. AMRs are fully aware of their surroundings and are not "blind" like AGVs. This influences choices about failure management, collision and dead-lock prediction and avoidance, and guide route selection. Environmental sensing enables an AMR
3. to help, work together, and communicate with both people and technology, which requires additional choices.
4. 4.1.1. The mechanics of robot locomotion A robot's kinematics, stability, and maneuverability are all significantly influenced by its locomotion system. The majority of AGVs provide a low-complexity and cost- effective trade-off against the aforementioned characteristics by having either two independently driven wheels with several omnidirectional supporting wheels or one steerable traction wheel in the front with supporting wheels in the rear. There are several AMR wheel or leg combinations, permutations, and arrangements. Powering Swedish or spherical wheels or adding more legs may provide a great degree of maneuverability, enabling the robot to travel in any direction along the ground plane at any moment, independent of its orientation (Siegwart et al., 2011). Wheeled AMRs are usually the primary option as many logistical tasks need for a high degree of steadiness. However, legged AMRs are usually used to try to maneuver in tough terrain. Legged AMRs for intralogistics tasks have been proposed by a number of businesses; Boston Dynamics' SPOT (https://www.bostondynamics.com/) and ANYbotics' ANYmal C are two examples. AMRs' enhanced mobility and placement flexibility necessitates the use of suitable route planning techniques, and the servicing sites must be accurately identified.
5. 5.1.1. Batteries Improved charging techniques and increased energy capacity, starting with traditional plug-in connection power supplies have a major influence on AMR battery management in relation to wireless power transmission. According to studies, wired connections are not always

necessary when wireless power transmission is used (Huang et al., 2018). Long charging durations and a small battery capacity were AGVs' weak points, which decreased their computational power, performance, and usage. Additionally, larger vehicles were needed to accommodate traditional lead-acid high-capacity batteries. Longer operating times and more power for the calculations required for autonomous navigation and operations are made possible by the new high-capacity batteries (such as lithium-ion). Additionally, they enable the AMRs to be smaller (this also applies to the most recent AGVs), which enables them to be placed in narrow aisles or even immediately under many loads that are densely stacked in deep lanes (Lamballais et al., 2017). Although battery management may still be important for round-the-clock operations, its significance has considerably decreased as a result of these technical advancements (Zou et al., 2018). Reliable system functions, such as battery management, have therefore attracted more attention from researchers. Furthermore, more rigorous scheduling choices are encouraged by the higher battery power.

5.1.1. *Manipulating equipment*

New services and material handling tasks may be carried out by integrating AMRs with various manipulating tools into a single unit. AMRs can select individual products and lift unit loads thanks to robotic manipulators (Shah et al., 2018). AMRs can work together to complete transportation tasks with humans and other AMRs (Lee & Murray, 2019; Machado et al., 2019).

Both short-term and long-term planning are required for the wide variety of functions that AMRs provide. This entails coming up with innovative ways to provide these services, creating strategies for AMR cooperation, and coordinating their scheduling with production schedules to guarantee collaboration at the appropriate time and location.

5.1.2. *Processing devices*

The AMR's ability to make judgments in real time allows it to navigate and function in a dynamic environment. Previously, mobile robots' ability to make intelligent decisions was limited by the substantial amount of processing power needed. AMRs can now make decisions in real time because to the development of ultra-low-power AI processors (Kim et al., 2017). These days, there are several sophisticated AI-focused CPU architectures available for visual identification of faces, bodies, gestures, objects, or scenes, such the Intel Nervana, NVIDIA Xavier, and Kneron AI SoC. Decision-making at the operational level in AMRs is particularly impacted by this trend. Making it possible to compute complicated decisions opens up new possibilities for dynamic scheduling and routing, navigation and classification, and effectively responding to impediments.

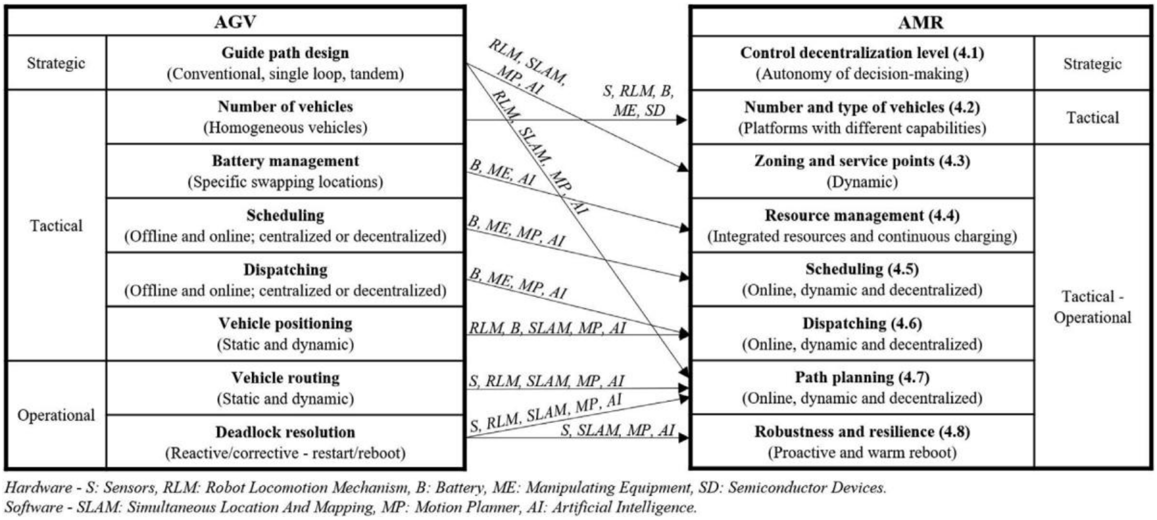
6.2. Software

6.2.1. Concurrent mapping and localization The two tasks of making thorough area maps of the surroundings and figuring out where an AMR is on a map are included in SLAM, a technique that supports real-time navigation (Bloss, 2008). While filtering the dynamic barriers, the mapping process creates a reference map using the 3D point clouds obtained from the scanning sensors. Combining the sensor data to pinpoint the AMR's position at any given moment has proved to be a challenging task. The use of Kalman filter technology has led to a breakthrough in recent years. To anticipate a robot's position and orientation, estimates from several sensor inputs must be merged to create a probability distribution across all potential robot positions (Bloss, 2008). The Kalman filter corrects the prediction over time using a recursive method. With the use of many measurement sources, measurement

It is possible to overcome problems with noise and sensor inaccuracy (Pratama et al., 2016). Global positioning systems that use network satellites in orbit can enable SLAM outdoors, while real-time location systems that use ultra- wideband technology can support it inside for high precision and dependability. The precise locations of the AMRs may be determined by using trilateration and multilateration.

5.1.3. *Motion planning*

6. Motion planning is a crucial component of equipment manipulation and vision-based



AGV		
Strategic	**Guide path design** (Conventional, single loop, tandem)	
Tactical	**Number of vehicles** (Homogeneous vehicles)	
	Battery management (Specific swapping locations)	
	Scheduling (Offline and online; centralized or decentralized)	
	Dispatching (Offline and online; centralized or decentralized)	
	Vehicle positioning (Static and dynamic)	
Operational	**Vehicle routing** (Static and dynamic)	
	Deadlock resolution (Reactive/corrective - restart/reboot)	

AMR	
Control decentralization level (4.1) (Autonomy of decision-making)	Strategic
Number and type of vehicles (4.2) (Platforms with different capabilities)	Tactical
Zoning and service points (4.3) (Dynamic)	Tactical - Operational
Resource management (4.4) (Integrated resources and continuous charging)	
Scheduling (4.5) (Online, dynamic and decentralized)	
Dispatching (4.6) (Online, dynamic and decentralized)	
Path planning (4.7) (Online, dynamic and decentralized)	
Robustness and resilience (4.8) (Proactive and warm reboot)	

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.

Collaborative robotics, a greater range of services offered, and big fleet numbers or fleet swarms have all put the central hierarchical structure to the test. A centralized control hierarchy lowers system performance since it has to make and convey several choices at once in a short amount of time. For example, hundreds of mobile robots may form a vast system in robotic mobile fulfillment (RMF) systems (Fig. 3(g)) (Wang et al., 2020). Thousands of mobile robots are operated by the biggest Amazon warehouses. These systems are often separated into modules that include vehicles, pickup and replenishment stations, and pods arranged in a grid pattern (Lamballais et al., 2020). By adding more cars or modules, the system may be readily expanded. By lowering high traffic and congestion levels, decentralized navigation and task distribution may assist in managing the large number and density of vehicles in such intralogistics settings. At the strategic level, decisions must be made on the extent of operational decentralization and AMR accountability.

The quantity of AMRs, including tools like manipulators, must be determined based on particular tasks and applications. Techniques for choosing and assessing the fleet's size and equipment in terms of cost, quality, productivity, and flexibility must be created. Vehicles may be introduced immediately when systems are ready, however, because of their quick installation timeframes.

Instead of following a predetermined route, AMR vehicles are able to choose their own route and drive freely within designated traffic zones. Therefore, the creation of a guide route is no longer required; instead, new choices must be made, such as establishing areas where AMRs may function independently (Fig. 2). The AMR has the ability to establish and modify these zones dynamically in a decentralized fashion or on a daily or weekly basis. Operational flexibility that maintains a high level of AMR responsiveness is made possible by the quick setup and simple zone changes. These zones allow for the easy addition, assignment, or configuration of service roles for short-term operations like item selection or human collaboration. To lessen traffic and the chance of accidents, the zones may provide travel instructions, traffic levels, and other pertinent information. Travel and lead times are significantly impacted by the locations of the service zone and service points. New guidelines for scheduling, patching, and allocating idle AMRs for optimal responsiveness are necessary due to the increased flexibility. AMRs can follow routes and handle materials that AGVs cannot because of the robot's locomotion mechanism and equipment.

AMRs can work in tandem with several robots to move blocking loads (as in Puzzle-Based Storage (PBS) systems; see Fig. 3(n)), climb shelves (as in some Autonomous Vehicle Storage and Retrieval (AVS/R) systems; see Fig. 6(o)), or decrease traffic (as in an RMF system). Approaches to route design must take this navigation flexibility into account.

AMRs must meet several requirements, like as safety norms, before they may be sold, much like any other intralogistics vehicle. They also need to be strong and trustworthy. At the moment, AGV systems need human oversight and assistance to function. Their sensitivity to a changing environment makes human mistake and failure management a top priority. AI can help AMRs bounce back from setbacks and identify ways to fix mistakes, making them more resilient. The traditional AGV decision areas have been replaced by the following for AMRs (Fig. 4) due to changes in the planning and control environment brought about by hardware and software developments: (i) the level of control decentralization; (ii) the quantity and kind of vehicles; (iii) zoning and service points; (iv) resource management; (v) scheduling; (vi) dispatching; (vii) path planning; and (viii) robustness and resilience. The next part presents the newly developed planning and control structure together with its decision areas. The transition from AGVs to AMRs and the associated choice dilemma are explained first in each section. Second, in accordance with the literature, we introduce and go over the modeling strategies for AMRs as well as the AGV techniques that apply to AMRs.

8. Methods for planning and controlling AMRs

8.1. *Control decentralization level*

Issue One of the most important strategic choices is the degree of control decentralization. When developing the interfaces between AMRs and their operational environment, it is essential to decide whether components of a system should be managed centrally or decentralized. For small-scale, straightforward systems, centralized control structures with a strong industrial foundation may access global data to achieve the best single- objective performance. For systems with many goals, decentralized control may often only access local data and identify local optimum solutions that are below ideal on a global scale (Fig. 5a). However, decentralized systems are necessary for complicated, large-scale systems (De Ryck et al., 2020a).

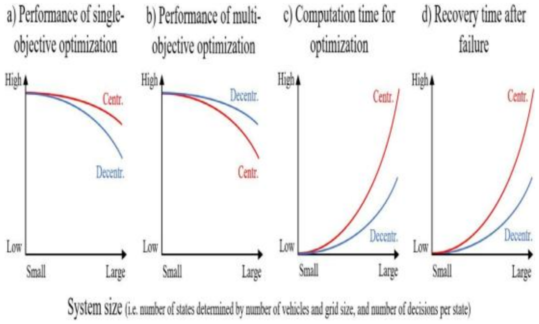


Fig. 5. Centralized versus decentralized control in small and large systems (partly based on Fauadi 2012).

Decentralized control may achieve excellent performance in a more unstructured environment with a wider range of actions since the optimization takes into account many criteria (Fig. 5b). several decision states must be taken into account in optimization techniques for big systems with several cars. Since decision-making is divided across many AMRs and only local considerations are taken into account, the calculation time is much less in decentralized control than in centralized control (Fig. 5c). Additionally, this enables a further decrease in the recovery period after failure (Fig. 5d). On the other hand, centralized control takes a long time to assess each AMR's condition after a failure and to plan the fleet's recovery. Thus, it is essential to provide techniques for identifying the best control decentralization level for the various decision- making areas, such as scheduling, zoning, or route planning, at the strategic decision level.

Methods

9. Previous research have introduced and examined AMRs with different levels of decentralization.

Wan et al. (2017) provide a cloud-based decision- making engine that can be shared among AMRs and has decentralized navigation (map processing) and centralized scheduling (job allocation). More central control over AMRs is made possible by the system's tiny size, and the cloud-based system can make judgments. The research highlights that although using simulation modeling based on the locations and statuses of the AMRs might enhance their energy efficiency, implementing basic AMRs and outsourcing the decision-making to the cloud can keep overall costs low. The relevance and viability of hierarchical control of AMRs have been examined via simulations and computer experiments (Demesure et al., 2017; Zhang et al., 2017). Kousi et al. (2019) examine the performance of an assembly line in the automobile sector using discrete event simulation. Centralized cloud-based systems are capable of identifying material supply needs, initiating material supply activities, scheduling them, and informing the AMRs of schedules. This minimizes vehicle travel distance and lowers the frequency of component depletion, which boosts assembly line productivity and makes effective use of available resources. Autonomously moving storage loads from input locations to the storage area or retrieving loads from storage to output points is possible with mobile robots in high- density PBS systems (Gue & Kim, 2007; Alfieri et al., 2012; Gue et al., 2014). The robots in these systems must work together to move cargo out of the way in order to build routes since they lack travel aisles. To transfer objects swiftly and without deadlocks, the robots divide and negotiate the transportation jobs. The decentralization of control regions beyond route planning has been the subject of a few studies. When compared to other material handling systems, AMRs might be a more affordable option that can be quickly implemented. AMRs may bid against or negotiate with other machines for work assignments in a decentralized task allocation system described by De Ryck et al. (2020a). According to Fragapane et al. (2020b),

To ascertain optimal configurations and the corresponding throughput performance effect of the AMR in production networks in comparison to conventionally balanced lines, mathematical modeling and parametrical analysis were used. AMRs are used in production networks to manage the connection of workstations during workstation outages.

of using novel approaches to evaluate and choose between centralized and decentralized control systems, the research of Maniya and Bhatt (2011) and Hellmann et al. (2019) provides further support. For multi-attribute selection procedures, Maniya et al. (2011) suggest combining an analytical hierarchy technique with a modified grey relational analysis method. Hellmann et al. (2019) provide a new paradigm that supports AMR design, operation, and control policy decision-making by combining failure modes and impacts analysis with analytic hierarchy procedures.

The main goals of analyzing centralized versus decentralized control structures are to minimize expenses while optimizing resource use and throughput. Although decentralizing decision-making for navigation is the most popular concept, decentralizing decision-making in a number of other areas may also boost AMR autonomy. A customized combination of centralized and decentralized control is necessary for each application area due to its distinct requirements. To provide a solid foundation for the quantity of cars and other pertinent needs, the level of autonomy in AMRs must be examined and decided at the strategic level.

9.1. *Number and type of vehicles*

Problem

Decisions on fleet size are traditionally supported by combining the study of the number of trips with AGV characteristics and the distances in the set guiding route. However, journey times and distances between service stations are very varied or even unpredictable because of the navigational flexibility of AMRs. Although AGV routing can only link two places inside the guidance route in a limited number of ways, AMRs' autonomous path-finding mechanism effectively expands the options. Currently, AMRs work in application areas where people may not be acquainted with AMR activities, including hospital visits. It is impossible to avoid congestion and heavy traffic, which will impair AMR performance and lengthen journey times. Therefore, new techniques are required to determine the appropriate number of vehicles. Different AMR kinds that range in size, function, or equipment within a same fleet are also made possible by the adaptable platform. At the tactical level, it is also necessary to decide on the kind of equipment and the quantity of vehicles. Techniques

Simulation and modeling in mathematics

The ideal number of automobiles to manufacture may be determined by mathematical modeling and simulation. Discrete event simulation is used by Ji and Xia (2010) to determine how many vehicles are needed for high utilization and to ensure system stability when the number of depots varies. According to Singh et al. (2011), The smallest number of vehicles required to satisfy the

the number and kind of vehicles necessary.

Modeling queuing networks

In queuing network modeling, a client enters a queue and, based on a routing mechanism, proceeds through a number of service operations in a network before leaving the system. The AMRs may be represented as a customer (closed queuing network), server (open queuing network), or as a semi-open queuing network that connects to a customer for certain activities. The various models provide varying potential applications. At the operational decision level, open queuing networks may be utilized to predict waiting times and

analysis of the container terminals' transportation infrastructure. It is possible to identify the ideal number of cars to reduce the overall cost of the investment. In order to optimize system throughput in a manufacturing or distribution setting, Choobineh et al. (2012) provide an analytical multi-class closed queuing network model that is expanded with simulation to identify the ideal number of vehicles and the ratio of loaded to empty trip durations. A closed queuing network model with simulation is also used by Roy et al. (2016) to examine how traffic affects the quantity of vehicles at container ports. Roy et al. (2020) calculate the number of vehicles with varying capacities at automated container terminals using open, closed, and semi-open queues. These studies' findings show that the quantity and kind of vehicles as well as throughput have a significant impact on vehicle congestion and speed.

The benefits of closed queuing networks (inner network with a population restriction) and open queuing networks (external queue to accept tasks whose entry is delayed) are combined in semi-open queuing network modeling. Incoming clients in an external queue may be matched with available resources in the resource queue via a synchronization station (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

throughput durations. Closed queuing

networks are suitable for estimating throughput capacity since they presume that the system is the.

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capability at the design level of a particular arrangement. Semi-open queuing networks are capable of both, but doing the (approximate) analysis requires a little more effort.

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Fukunari and Malmborg (2008) use an open queuing network model to evaluate the cycle time and resource usage for AVS/R systems. Performance is estimated by an iterative computational approach.

It has a repeating pattern of the matrices A, B, and C and is almost block-tridiagonal. The matrix-geometric technique (solving for π Q = 0 with π 1 = 1) may be used to determine the system's state probability vector π, from which performance metrics can be calculated. To solve for π, one must calculate the so-called rate matrix R from the equation.

scheme that takes random storage assumptions into consideration. Yuan and Gong (2017) determine the optimal number of robots, their speed, and

C_1 plus$RB_1+RA_2=0$

Provide RMF design specifications. Wang et al. (2020) use analytical methods, such as an open queuing network model and a bottleneck-based model, to simulate robotic mobile fulfillment system architecture possibilities and calculate the optimal number of vehicles. Zhang et al. (2020) use open queuing networks and discrete event simulation to investigate the effects of robot capacity on the functioning of a flexible flow shop with random and state-dependent batch transport. Open queuing networks are unable to reflect the aggregate capacity constraint imposed by the AMRs involved in several operations. Limiting the resources, like in a closed queuing network, allows one to concentrate on the population constraint. Fukunari and Malmborg

(2009) propose a closed queuing network approach to assess resource utilization in AVS/R systems. Hoshino et al. (2007) state that the simulation and model of closed queuing networks 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 $R_{(n)} = -(C_1 + R^2 A_2\ )B^{-1}$. 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 net- work. The performance of the external queue length as well as the average number of transactions in the network (including wait- ing 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 ex- tended algorithm (Ekren and Heragu 2010). The study by Zou *et al.* (2016) calculates the number of robots with lifting and transport capabilities that can move on a tiny warehouse's grid roof using semi-open queuing networks to estimate system throughput time and cost. All things considered, mathematical optimization, simulation, and queuing networks have proven to be effective ways to model the industrial environment with its unique constraints, analyze operating systems, and assess the number of vehicles. The primary goal is to maximize system throughput, while the secondary goals are to distribute workload, minimize throughput time, travel time, and expenses.

9.2. *Zoning and service points*

Issue

The design of zones and service points must be decided upon in order to move from offering services along set guide pathways to flexible regions. The quantity and placement of service stations may be determined dynamically in some AMR application areas. Examples include cooperative fetchers in warehouses, RMF systems, and guide help in hospitals or shopping centers. Cost and productivity performance may be increased by separating the service regions into various zones with one or more vehicles. Because only brief excursions are made and cars are accessible more quickly, limiting each vehicle's operational area enhances the system's overall responsiveness. Consequently, zoning includes the following decisions and activities: (I) assessing the area where the service must be rendered; (II) identifying fixed and/or dynamic service points; (III) establishing zones (adding, removing, dividing or overlaying zones, and defining flow direction); and (IV) figuring out how many vehicles are allowed in each zone. These stages might be taken in different order.

Methods

To increase production system performance, a number of studies recommend that zones be set up in blocks or loops and that d$^{(}$e^{n-}li$^{1)}$very^{1} and pickup locations be grouped t o| g ether. Z|o| ne segmentation and tandem transportation system selection are examined by Shalaby et al. (2006). They use a heuristic approach to achieve many goals, including reducing the frequency of between-zone excursions, achieving the maximum workload, and reducing handling costs and overall flow distance. To build a unidirectional flow loop, Asef-Vaziri et al. (2007) provide precise optimization, decomposition, and heuristic strategies. Both minimizing empty vehicle trip lengths and optimizing loaded vehicle travels are made possible by a neighborhood search heuristic approach and a binary integer programming paradigm. In order to minimize the total distance traveled, Farahani et al. (2007) analyze the flow route design and use a genetic algorithm to identify the best site for the loop and the pickup and delivery points. In a computer experiment, ElMekkawy and Liu (2009) optimize the partitioning issue in a tandem AGV system by preventing bottlenecks, distributing the work across zones, and lowering the total load using a memetic approach. The flow pattern and the locations of pickup and delivery sites should be modeled and created using a cutting-plane algorithm, according to Hamzeei et al. (2013). The traveling salesman issue, which involves finding the smallest loop that passes over at least one edge of each workstation, is examined by Asef-Vaziri and Kazemi (2018). Robust loop design solutions that maximize loaded and decrease empty vehicle travel are achieved by their suggested evolutionary method.

Additional performance enhancements might be obtained by simultaneously analyzing other zone and design combinations. Tubaileh (2014) employs a simulated annealing technique to examine various production systems via simulations in order to determine the best locations for machines in every possible configuration. The project's goal is to shorten material handling system trip durations. Zones are established and warehouse layout is examined by Qi et al. (2018).

based on the task density. Reducing total waiting time, total trip time, and total distance traveled is made simpler by their methods. To increase system performance, they advise distributing the storage of frequently moved or in-demand items evenly. Zoning in warehouses may save a significant amount of money, claim Lee et al. (2019). To reduce the amount of time required to move each item from a pick list to the packing station, order-picking robots' zone, service point, and warehouse layout configurations are examined using MILP and numerical analysis. In order to increase system throughput, average order cycle time, and robot usage, Lamballais et al. (2017) and Roy et al. (2019) study zone assignment techniques in RMF systems using simulation and queuing network models. Lamballais et al. (2020) employ a semi-open queueing network with simulation to find the ideal number of pods, picking stations, and replenishment stations in order to study the proper number of service points in such systems. In order to examine the effects of vehicle placements and zones within a tier employing different vehicle classes and class switching probabilities on throughput performance, Roy et al. (2012) suggest a semi-open queueing network approach for AVS/R systems. Azadeh et al. (2020) dynamically modify the number of zones in a human-robot collaborative picking system by integrating a closed two-phase server queuing network into a Markov decision process. They demonstrate how the throughput capacity of multichannel warehouses with different numbers of big and minor orders may be increased by dynamically altering the number of zones.

Overall traffic may be impacted by zoning variations and the quantity of cars per zone. Reducing traffic between cars may assist cut down on total travel time and improve system responsiveness by minimizing the amount of time that cars must spend navigating intricate traffic conditions and clearing bottlenecks in crowded regions. Zone partition design and dynamic zone management are two components of the dynamic zone technique put forward by Ho and Liao (2009). According to their modeling findings, there is less traffic overall and better load balance between cars in various zones. Azadeh et al. (2019b) estimate the throughput effect on vehicle obstruction by analyzing various zoning systems and access control rules using closed-queuing network models. Singh et al. (2011) recommend the use of discrete event simulation and a technique for dividing the whole space into zones that are only accessible by certain vehicles in order to optimize throughput in an automobile manufacturing facility. In a manufacturing setting, Małopolski (2018) provides a technique for enhancing transportation performance for unidirectional, bidirectional, and multiple-lane flow route systems by first dividing the layout into a rectangular grid and then using simulation and linear programming.

The main objectives of creating zones and service points are to decrease travel distance, traffic, and throughput time while distributing the load across the system in order to improve and, ideally, maximize system throughput and resource usage. In dynamic zones with many and fluctuating service points, the usage of previous AGV-based approaches is limited, and the complexity of AMR modeling is raised. Changes in service point locations impact workload and service requirements. More variables are therefore included in mathematical models, which negatively impacts computation time and usefulness. In these situations, simulation and evolutionary methods seem to be the most appropriate. A different possible approach has been used to represent the assignment of mobile robots in warehousing. There are several service points (picking sites) in warehouses, and they vary based on the orders that need to be completed. A potential combination of techniques that can accurately and computationally address complicated and dynamic issues is queuing network modeling, which is used to predict performance, and Markov decision procedures, which are used to allocate cars dynamically. They may also be used in other fields of application, such 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 exten- sions 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.

9.3. *Resource management*

Problem

Because they only have one handling unit, current AGVs can only do a limited number of handling tasks, such as lifting and moving. However, equipment swapping is widespread in flexible manufacturing and robots. AMRs have the ability to charge or swap batteries, load, utilize, unload, and interchange equipment. Numerous materials are available for usage and sharing on the AMR platform. For these resources to be used as efficiently as possible and, therefore, for high AMR productivity performance, the decision-making procedures of location planning, scheduling, and dispatching are crucial.

Methods

The location of charging stations still has to be determined, despite the fact that batteries' energy density is rising. Boysen et al. (2018) look at how makespan performance is affected by battery capacity, charging periods, and the quantity and placement of charging stations. To determine the best charging spots in terminals, they suggest computer tests using a genetic algorithm. According to a study by Kabir and Suzuki (2019), performance in terms of total travel distance and waiting time at a battery station can be impacted by the four heuristics of (I) choosing the nearest battery station, (II) choosing a battery station that will cause the least delay taking into account both travel time and waiting time in a queue, (III) choosing the nearest battery station on the current route, and (IV) choosing the farthest reachable battery station on the current route. According to their simulation, a production system's productivity may be raised by making decisions regarding battery switching more often. In an RMF system, Zou et al. (2018) assess battery charging and switching tactics. Comparing various solutions in terms of cost and throughput time performance is made possible by the use of simulation and a semi-open queuing network. The research highlights that inductive charging provides the greatest performance and that the battery recovery strategy chosen might have a considerable impact on throughput time performance. An AMR may independently decide when to visit a charging station and how long to charge under the decentralized charging strategy proposed by De Ryck et al. (2020b). A general restricted optimization technique is used to solve their method, which is described as an extension of the traveling salesman problem in industrial systems. To improve resource efficiency, they look at various charging plans and charging station selections.

In the foreseeable future, planning and regulating AMRs will depend more on effective resource management. AMRs will have access to and utilize a large variety of equipment, which necessitates efficient management and utilization, while AGVs use a limited range of handling equipment. Without some kind of coordination, completely delegating resource management to the AMRs will result in less than ideal system-level outcomes. Achieving a near global optimum requires sharing the findings across many units and iterating the decentral optimization choices for all AMRs. Short travel times may be achieved by using the outcomes of decentralized operational level decision-making to inform tactical choices like where to locate battery storage facilities or equipment storage sites. To address these choices concurrently or iteratively, new modeling techniques for AMRs are required. Additionally, predictive analytics may help determine when batteries should be charged or

When should the mounted equipment be switched to a time when there is the least chance of conflict? There are currently no studies that provide approaches that take operational information sharing into account while making such judgments.

9.4. *Scheduling*

10.Issue

The decision-making process for scheduling material handling systems with machines, people, equipment, components, and containers at the same time is supported by a sizable body of literature. Most studies in manufacturing use mixed integer programming models with heuristic algorithms and focus on a small number (less than 50) of vehicles under centralized, hierarchical management. Since there are usually more jobs and a greater variety of activities in production than in a warehouse, mathematical modeling and optimization techniques have been developed extensively to address scheduling issues. In order to confirm and generalize their findings, a few of the publications have additionally included simulation models. Thanks to advancements in computational capacity, a new line of study is now able to employ AI approaches, such as evolutionary algorithms. Decentralized scheduling techniques that allow AMRs to bid for or negotiate assignments are still rare, nonetheless.

Techniques

Transportation activity scheduling using mathematical modeling

The influence of scheduling "only" cars on the production system's performance has been examined. Since resolving dispatching issues seems to be the main emphasis of these application domains, there aren't many publications that concentrate on container terminals and warehousing. Decomposition techniques (Corréa et al., 2007) and mathematical and statistical models (Ghasemzadeh et al., 2009) have been used in manufacturing systems to solve and analyze the relationship between scheduling rules and conflict-free vehicle routing and the effect on production delays. Using two-step algorithms to cluster the solution space and then identify the best solution, other authors have examined the effects on makespan, cycle time variations, and vehicle earliness and tardiness (Fazlollahtabar et al., 2015; Bakshi et al., 2019). Simulation is used to assess various scheduling approaches for increasingly complicated issues including heterogeneous and multiple-load vehicles (Ho & Chien, 2006; Bocewicz et al., 2019). An extended simplex algorithm and greedy vehicle search have been used to solve a minimal cost flow model for scheduling transportation operations in container terminals (Rashidi & Tsang, 2011). In order to solve the multi-aisle access scheduling issue, Polten and Emde (2020) propose two access policies: exclusive and parallel access. They concentrate on warehouses with very narrow aisles. The robot work allocation issue is analyzed and optimized using a MILP and a large neighborhood search method.

Techniques for scheduling cars and machinery together

To achieve high overall efficiency in the manufacturing system, tasks in machine centers and vehicles should be scheduled simultaneously. Reducing wait times, transportation expenses, and makespan are the primary goals. The problem's complexity necessitates the use of simulated annealing approaches, general heuristics, decomposition algorithms, and adaptive genetic or memetic algorithms (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). While Lyu et al. (2019) employ simulation to examine the effects of scheduling policies on makespan and vehicle utilization, Fazlollahtabar (2016) and Fazlollahtabar and Hassanli (2018) use a mathematical cost flow model and modified network simplex technique. Yang et al. (2018) examine the simultaneous scheduling of many cranes and trucks in a container yard in the context of a container terminal in order to reduce the duration of loading and unloading containers utilizing

11. A genetic algorithm. In order to address inter-robot restrictions and appropriately represent the intricate relationships between container terminal agents, Chen et al. (2020) suggest a multicommodity network flow model. The system's average makespan and each robot's average resource transfer time may be reduced by using a genetic algorithm.

AI-based approaches to constraint or multi-objective problems

The usage of multi-objective or constraint scheduling models has become more practical as a result of advancements in computing power and the use of AI approaches. This is especially true in complex situations like manufacturing with several workloads and machine centers. Some authors have created algorithms for genetic and ant colony optimization (Udhayakumar & Kumanan, 2010; Saidi-Mehrabad et al., 2015), a whale optimization algorithm (Petrovic´ et al., 2019), hybrid evolutionary or genetic algorithms, a sheep flock heredity algorithm (Anandaraman et al., 2012), and particle swarm optimization (Gen et al., 2017; Mousavi et al., 2017; Rahman et al., 2020). The hunting of humpback whales served as the model for the whale optimization method. In the exploration phase, it initially searches the "ocean" for "prey." This is equivalent to agents shifting positions while exploring the state space in an attempt to locate global optima. They halt when they find a place close to a global optimum. Following the first stage, the whales begin spiraling downward to capture their prey. We refer to this as the exploitative phase. The agents in the algorithm follow a "leader" and update their position data as they move toward the end destination based on a shrinking encircling mechanism. These techniques work well for resolving multi-objective issues that combine, for example, maximizing battery charging efficiency and vehicle usage with minimizing makespan, trip time, and tardiness.

Techniques for work distribution and decentralized scheduling

A novel information processing technique for online machine and vehicle scheduling is provided by current computing and information sharing technologies, opening up new levels of flexibility and agility. Decentralizing job allocation requires high levels of communication and connection. In order to decentralize work allocation, Zeng et al. (2018) provide a cooperative and distributed scheduling method based on dynamic communication between machines and cars via a hormone-regulation mechanism. Auction-based approaches, in which an announcer (machine) and bidder (AMR) collaborate to achieve high performance in work distribution, provide a novel and promising approach in decentralized scheduling. De Ryck et al. (2020a) categorize various auction-based job allocation techniques into single, bundled, and combination items that are offered for bid in parallel or sequential auctions. Since it represents the cost for the AMR to do the particular work, the bid computation is an essential component for scheduling and task allocation. AMRs may bid on new jobs while working on a current task, which allows them to locally optimize the task list and utilize that information to determine the next bid. One way to compute bids is to use the cost to
11.1. carry out the duties assigned by the AMRs or on the marginal cost while taking the other activities on the list into account. There is a bidding algorithm that works well for each sort of calculation. CNET, OCA-Alloc, CBAA, and CBBA are used for the first kind of cost, while Prim Allocation, SIT-, and SET-MASR algorithms employ marginal cost (for a summary, see De Ryck et al. 2020a). These action-based techniques provide flexibility and scalability while overcoming the drawbacks of earlier OR approaches and applying to big car fleets. Due to the distributed nature of the computation, it may be used to solve very complex problems with several constraints. Each AMR has a correspondingly higher demand for processing power, which has a detrimental effect on battery life. The integration of this decision area with dispatching and resource management will provide more opportunities to improve these techniques.

11.2. Dispatching

Issue

Performance may be improved by using intelligent dispatching techniques that enable AMRs to be at the point of demand before a real need is declared. New chances for positioning and cruising when an AMR is idle are made possible by autonomous navigation's improved flexibility in reaching a large region and allowing for free positioning. AMR positions and demand data must be analyzed by a system in order to centralize the decision-making processes for AMR distribution and dispatch. Demand analysis using machine learning and big data may help optimize vehicle allocation across the system. However, in order to evaluate and transmit in real time, large-scale AMR systems need a lot of processing power. High-power cloud computing will be less necessary if this process is decentralized. Based on data exchanged with surrounding AMRs and past data, each AMR will maximize the time it has available. Negotiations and constant communication will maximize AMR's capacity to respond swiftly to requests.

Methods

Numerous multi-attribute dispatching rules have been developed to allocate workloads to the appropriate AMRs, mostly via the use of simulation, queuing networks, and mathematical modeling to evaluate them. Very few of them are seen in storage and container terminology; most of their uses have been in manufacturing.

Numerous methods, including route layouts, vehicle capacity and restrictions, and single or multiple objectives, such lowering delays, makespan, and travel time, have been used to quantitatively describe the complexity of the dispatching problem. Ventura and Rieksts (2009) developed a dynamic programming technique to handle idle vehicle position in a single loop AGV system. Ventura et al. (2015) expand the problem to a wide guide-path architecture and solve it using a genetic algorithm. Bozer and Eam-rungroj (2018) provide an analytical methodology to assess the throughput performance and device usage of various dispatching rules by modifying layout configurations in trip-based systems. For increasingly complex problems with several objectives and extra restrictions, heuristics like genetic and evolutionary algorithms have been used (Lin et al., 2006; Umar et al., 2015; Miyamoto & Inoue, 2016; Gen et al., 2017). Although it is less often used in manufacturing systems, queuing network modeling is routinely utilized in warehousing, especially for RMF systems. In an extended analysis of closed queuing network models, Smith (2015) investigates optimal task allocation in manufacturing systems with multiple transportation servers, infinite-capacity workstations, and a restricted capacity state. Zou et al. (2017) use a two-phase approximation technique and semi-open queuing networks to assess the retrieval throughput time performance of RMF systems. An assignment rule based on workstation handling rates is managed using a neighborhood search approach to get a virtually optimum assignment. He et al. (2018) provide a differentiated probabilistic queuing approach and use an alternating minimization technique with simulated annealing to minimize the weighted delay of each client order. Simulation has been used to examine a range of scenarios in order to provide decision makers general advice and conclusions, especially in manufacturing where complex difficulties abound. Some authors focus on evaluating the impacts of numerous multi-attributes dispatching rules (Bilge et al., 2006; Guan & Dai, 2009; Singh et al., 2011; Confessore et al., 2013; Zamiri & Choobineh, 2014). Characteristics including waiting time, input and output buffer size, travel time or distance to the pick-up location, and the use of single-load or multiple-load vehicles are often included in these rules. The constraints and demand characteristics of the operating environment have a substantial effect on AMRs' response. For multi-scenario analysis, simulation has shown to be an effective tool that can be used with big data analytics and machine learning methods.

13.2. Planning the pathIssue

In order for the AMR to move autonomously between locations, maybe even in a huge swarm, route planning is the process of determining a continuous, deadlock-free path with minimal congestion delay from the beginning to the objective point. route discovery for AMRs employs a description of the environment to mathematically determine the shortest and conflict-free route, in contrast to AGV routing, which takes a guide path as input. Every time an AMR moves from one location to another, it forges a brand-new, distinct route. To determine the best course with one or more goals, constraints on robot size, lane dimensions, speed, possible curvature, and static and dynamic impediments may be added. route planning is often done only once in static settings, but in dynamic environments, it may be necessary to repeat the process of locating a route free of collisions many times in order to accommodate several vehicles avoiding the obstacles or removing them.

Techniques

The path-finding techniques may be divided into three categories: accessibility limitations for a single vehicle, multiple vehicles, and multiple vehicles with unit load (i.e., impediments must be eliminated).

Techniques for a single car

The graph representations of the environment and graph search methods for a single AMR are described by De Ryck et al. (2020a). According to their research, the most often used graph search algorithms for determining the shortest route are the A∗ and D∗Lite algorithms, which are variations of Dijkstra's algorithm.

Compared to Dijkstra’s algorithm which allows to prioritize di- rections (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 objective state. The D-Lite algorithm, which is particularly helpful for determining the shortest route across vast and complicated locations, operates in the opposite direction from the destination to the start when compared to the previously described methods.

As of right now, simulation cannot accurately replicate the AMR pathways and behavior in dynamic environments, claim Liaqat et al. (2019). There are several circumstances in a dynamic environment when the AMR's passage may be momentarily blocked by moving barriers. Experiments in their investigation back up the AMR motion planning reaction to steer clear of obstructions. They provide procedures that enhance route planning simulation quality and accuracy in dynamic environments.

Techniques for several cars

Due to limitations like traffic or stalemate, the shortest route does not always translate into the lowest trip time in intralogistics systems with several cars. Numerous research use mathematical modeling to provide conflict-free or deadlock-free approaches for solving combinatorial problems and determining the shortest route (Wu & Zhou, 2007; Saidi- Mehrabad et al., 2015; Yang et al., 2018).To assign workloads to the right AMRs, a variety of multi-attribute dispatching algorithms have been created; they have mostly been evaluated by mathematical modeling, simulation, and queuing networks. The majority of their applications have been in manufacturing; only few are found in storage and container terminology. The difficulty of the dispatching issue has been quantitatively described using a variety of techniques, such as route layouts, vehicle capacity and limits, and single or multiple goals, such as reducing delays, makespan, and trip time. A dynamic programming method was created by Ventura and Rieksts (2009) to manage the location of idle vehicles in a single loop AGV system. Ventura et al. (2015) use a genetic algorithm to tackle the challenge after expanding it to a broad guide-path design. By altering layout configurations in trip-based systems, Bozer and Eam-rungroj (2018) provide an analytical technique to evaluate the throughput performance and device utilization of different dispatching rules. Heuristics like genetic and evolutionary algorithms have been applied for more complicated problems with multiple goals and additional constraints (Lin et al., 2006; Umar et al., 2015; Miyamoto & Inoue, 2016; Gen et al., 2017). Queuing network modeling is often used in warehousing, particularly for RMF systems, although it is less common in manufacturing systems. Smith (2015) examines optimum task allocation in manufacturing systems with numerous transportation servers, infinite-capacity workstations, and a constrained capacity state in a more thorough examination of closed queuing network models. Zou et al. (2017) evaluate the retrieval throughput time performance of RMF systems using semi-open queuing networks and a two-phase approximation approach. To get a nearly optimal assignment, a neighborhood search technique is used to maintain an assignment rule based on workstation handling rates. In order to reduce the weighted delay of every client order, He et al. (2018) provide a differentiated probabilistic queuing strategy and combine simulated annealing with an alternating minimization technique.

Particularly in manufacturing, where complex challenges abound, simulation has been utilized to analyze a variety of situations in order to provide decision makers broad recommendations and findings. Some writers (Bilge et al., 2006; Guan & Dai, 2009; Singh et al., 2011; Confessore et al., 2013; Zamiri & Choobineh, 2014) concentrate on assessing the effects of multiple multi-attributes dispatching rules. These regulations often include characteristics like waiting time, input and output buffer size, journey time or distance to the pick-up site, and the usage of single-load or multiple-load trucks. The operational environment's limitations and demand characteristics have a significant impact on the responsiveness of AMRs. When combined with big data analytics and machine learning techniques, simulation has shown to be a useful tool for multi-scenario analysis.

13.2. Making a plan Problem

Route planning involves figuring out a continuous, deadlock-free path with the least amount of congestion delay from the starting point to the destination point so that the AMR may travel independently between sites, perhaps even in a large swarm. Unlike AGV routing, which uses a guide path as input, route discovery for AMRs uses an environment description to mathematically find the shortest and least conflicting path. An AMR creates a fresh, unique path each time it travels from one place to another. Limitations on robot size, lane dimensions, speed, potential curvature, and static and dynamic obstacles may be applied in order to find the optimal path with one or more objectives. In static environments, route planning is often done only once. However, in dynamic situations, it can be essential to repeat the process of finding a collision-free path many times in order to accommodate multiple vehicles avoiding or eliminating obstacles.

Techniques

Accessibility restrictions for a single vehicle, multiple vehicles, and multiple vehicles with unit load (i.e., obstacles must be removed) are the three categories into which the path-finding algorithms may be separated.

Methods for a single vehicle

De Ryck et al. (2020a) provide the graph representations of the environment and graph search techniques for a single AMR. Their study indicates that the A∗ and D∗Lite algorithms, which are variants of Dijkstra's algorithm, are the most often utilized graph search methods for figuring out the shortest path.

11.3. Robustness and resilience

Issue

AMRs' capacity to function without human oversight or intervention and to bounce back from failures is a critical feature that ensures a strong and resilient system. Studying the internal and external elements that impact system reliability is thus essential, as is implementing decision-making techniques that enhance AMR planning and control capabilities.

Techniques

Travel time uncertainty may potentially rise as a result of AMRs' enhanced navigational flexibility. Fazlollahtabar and Olya (2013) present a cross-entropy approach to describe the issue and provide a heuristic statistical strategy to calculate overall stochastic material handling time. 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. A manufacturing system's optimal, dependable production time and cost may be found with the use of bi-objective stochastic programming. The capacity of AMRs to respond to reliability difficulties has only been assessed in a small number of studies. Yan et al. (2017) apply a failure modes effects and criticality analysis and Yan et al. (2018) propose predic- tive maintenance strategies for the long-term reliability and stabil- ity of the system. Petrovic et al. (2019) advise balancing AMR consumption and activities to ensure continuous system performance. The suggested regulatory change has the potential to enhance maintenance efficiency and extend the AMR life cycle.

In simulation research, human dynamic interactions are often overlooked. Using historical material handling data, Fragapane et al. (2019) provide an agent-based simulation model for hospital vehicle use. This makes it easier to analyze how the dynamic environment affects performance deterioration during peak traffic times and core business hours. Simulating intricate logistics networks and comprehending real-world systems with several independent decision-making units are two areas in which agent-based simulation excels. Fransen et al. (2020) developed a dynamic route planning technique that aids in AMR recovery from impasse scenarios and boosts system resilience in response to the growing quantity and density of vehicles in grid-based systems.

Widespread acceptance of decentralizing the decision-making process and assigning decisions to AMRs will depend on the overall reliability of the system. Sturdy mechanisms that provide predictable outcomes are required. All AMR risks must be analyzed to discover, re- fine, and propose methods so that AMRs can achieve reliable per- formance in various different environments.

12.Research agenda for AMRs

13.14.1. Strategies and techniques for organizing and managing AMRs

In accordance with Section 4, we have categorized and organized all 108 reviewed publications according to the decision area, primary goals, techniques,

and the field of application. Table 1a, which covers Sections 4.1–4.4, and Table 1b, which covers Sections 4.5–4.8, provide a thorough overview of every evaluated article. Several times, articles that are debated and cited in various decision areas are brought up. The tables' insights for each decision area are highlighted in the paragraphs that follow. The section concludes with a summary and overview of all decision areas (Table 2).

Research interest in decentralized decision-making (Section 4.1) has grown. Few research, nonetheless, have looked at whether decentralized material handling control is more effective than centralized control or whether it is profitable. Simulation modeling has been the preferred approach up to this point since system throughput and throughput time are the key performance metrics that determine the control decentralization level (6/11 articles). Because Industry 4.0 strongly encourages decentralizing material handling, the majority of research has been done in manufacturing rather than other intralogistics domains (7/11 articles) (Furmans et al., 2018). Therefore, further research is required to examine and compare global vs local optimization, centralized versus decentralized control, and various levels of decision-making autonomy. The effects of decentralized control on profit, resource efficiency, responsiveness, latency, and system resilience and dependability need more study.

The wide range of AMRs (see Fig. 3) necessitates the use of various equipment types and decentralization degrees. By examining the intralogistics system with system throughput and throughput time as the primary goals, followed by waiting time, utilization, and cost, simulation modeling and queuing networks have aided decision-making on the quantity and kinds of AMRs (Section 4.2). Container terminals have drawn the greatest interest in this decision-making sector, despite the fact that the majority of research treat production and warehousing equally. AMRs using lifting or carrying equipment are the subject of the majority of the examined studies. There is currently a shortage of techniques for evaluating, improving, and supporting decision-making for the diverse fleets and equipment.

Mathematical modeling has been used almost solely in the zoning and service point choice area (Section 4.3) to analyze manufacturing intralogistics systems in order to better distribute workload and boost AMR utilization. Queuing networks, on the other hand, have mostly been utilized in warehousing to boost system throughput and reduce retrieval time due to journey time. Dynamic techniques are needed for zoning flexibility and service point placement. Only two studies, nevertheless, have suggested dynamic techniques. Azadeh et al. (2020) use a closed two-phase server queuing network incorporated in a Markov decision process to boost throughput capacity, whereas Ho et al. (2009) utilize heuristics/meta-heuristics and a simulated annealing technique for load balancing and traffic reduction. More dynamic approaches are required to swiftly adapt to variations in service location, such as shifts in hospital treatment need or product demand in storage. Rarely thought of in this decision-making domain, AI algorithms may support optimization techniques to enhance the existing deficient responsiveness, resource consumption, and dependability. Decentralized techniques may also let AMRs negotiate zones or ask for assistance when necessary to manage demand changes. Resource management has only been the subject of four studies (Section 4.4). These studies provide decision assistance and optimization techniques to enhance a range of manufacturing and warehouse performance metrics. The administration of the equipment installed on top of the car has gotten little attention in the present research, which mostly concentrate on scheduling battery charge and placing charging stations or inductive charging lines.

Future research will need to provide multi-objective optimization techniques for scheduling equipment sharing among a fleet and decision assistance for determining where to store shared equipment. AMR availability might be increased via battery and equipment optimization techniques, which would save expenses and boost output.

With 29 publications, scheduling loads and vehicles (Section 4.5) has drawn the greatest attention in the literature. With an emphasis on makespan and delay minimization, the majority of applications are found in manufacturing (25/29 publications). Numerous optimization methods and mathematical models have been presented and studied (26/29 articles). AI-based techniques like evolutionary algorithms, genetic algorithms, memetic algorithms, and swarm intelligence-based techniques like the ant colony approach, particle swarm optimization, sheep flock heredity algorithms, and the whale optimization algorithm have been used extensively in comparison to other decision areas. In contrast to scheduling, dispatching (Section 4.6) has concentrated more on simulation modeling and queuing networks to enhance the primary goals of responsiveness and makespan. While dispatching techniques are more often used in warehouses, scheduling is utilized at container ports. But optimization techniques for

concurrent scheduling and route planning (Corréa et al., 2007; Ghasemzadeh et al., 2009; Nishi et al., 2011; Petrovic´ et al., 2019), or concurrent scheduling and service point placements (Singh et al., 2011; Małopolski, 2018). This enables us to assess the many choices and comprehend their interactions in order to create more well-rounded choices. For example, by examining how to share the equipment installed on top of the vehicle, study on the quantity and kinds of vehicles and resource management may enable lower costs and higher utilization. This affects how many cars are needed. Additionally, robustness and resilience, route planning, and dispatching may all contribute to an intralogistics system's increased uptime. In order to provide a strong and durable intralogistics system in the event of an AMR failure, it is feasible to examine how swarm behavior may be used to dispatch and navigate additional AMRs by examining these decision areas concurrently. Additionally, zoning and dispatching or zoning and scheduling decision regions have to be examined concurrently. In contemporary research, one decision area's result serves as the other's input data. Simultaneously optimizing various choice areas would provide a greater range of options and make it possible to find and reach a new optimum. Multi-objective optimization may be solved with the help of AI approaches. routing and scheduling with an emphasis on resource use and (Petrovic) and are particularly helpful for integrating (et al., 2019).

Reliability is still inadequate. There are also insufficient optimization techniques for cheduling and dispatching in other intralogistics systems.

In recent years, there has been a growing interest in the route planning decision area (Section 4.7). 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 anufacturing and introduced heuristics improving the over- all 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 man- ufacturing 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 meth- ods are needed to support autonomous material handling systems to react appropriately in case of failures and to work indepen- dently 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 maximation (see Table 2). Mathemati- cal modeling is the most frequently applied method for long-term decisions in decision support and for short-term decisions for opti- mization 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%), dispatching (12%), control decentralization (8%), robustness and resilience (5%), zoning and service points (14%), and resource management (3%).

Numerous studies indicate that addressing several choice factors at once, such zoning and vehicle numbers, has a significant potential to increase performance outcomes.

decision-making domains, such dispatching and zoning, with goals pertaining to journey time, cost, responsiveness, resource consumption, and system throughput. The majority of intralogistics research on AMRs has focused on manufacturing and warehousing applications. Little focus has been placed on other intralogistics applications (Table 2). Nonetheless,

14.robust, proactive, scalable, and adaptable system. The following need to be on the research agenda for the future:

- Additional research is required to help determine which operations should be decentralized and centralized, how much autonomy the AMR should have, and under what conditions performance benefits should be granted. Particularly in emerging AMR application areas, multi-scenario analyses and agent-based simulations are interesting techniques that may aid in improving the decision-making process. Self-regulating, self-governing resource units that adhere to a set of predetermined rules in order to accomplish their goals while interacting with one another and their environment system are used in agent-based simulation. This approach makes it possible to integrate various degrees of decentralization.
- Since AMRs are expanding their services and entering new intralogistics settings, new methods are required to assess the number of vehicles. To find the ideal number of vehicles, methods that take into account the uncertainties of a dynamic environment—such as traffic, changing travel routes and distances, varied service sites within a zone, and various service activities—are required. Furthermore, techniques are required to determine the ideal proportion of various AMR types in a fleet. This may be supported by simulation modeling in conjunction with big data, machine learning, and predictive analytics. Moreover, the analysis of total obstacle avoidance as a factor in determining performance increase or degradation may be aided by queuing, flow, and traffic theory.
- New decision-making models are required for AMR equipment management. In addition to new application areas, integrated scheduling of manufacturing and warehouse operations will be greatly aided by AMR technology. Consider models where vehicles with several pieces of equipment work together, or where tools or equipment may be switched out to do certain jobs.
- AMRs may be quickly incorporated into new surroundings; new techniques are required to assist decision-making about the best way to organize and share equipment in intralogistics systems. 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. In order to achieve intelligent, decentralized distribution, AMRs may also exchange demand trends and engage in negotiations.
- Large-scale AMR systems (e.g. Amazon warehouses with thousands of interacting AMRs) will inevitably rely on decentralized scheduling. As a result, new strategies and tactics beyond auction-based work distribution have to be put forward. 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 indepen- dently without human surveillance in case of failures. Fresh predictive methods for e.g. maintenance will support AMRs to work proactively to reduce the number failures.

15.Conclusion

AMRs' technology advancements have greatly aided in achieving operational flexibility as well as improving quality, productivity, and sometimes cost effectiveness. AI-assisted decision-making encourages the decentralization of AMR-related tasks. Particularly in those application areas where suppliers have gained experience in previous implementation projects, the systems may often be implemented quickly. It is still challenging to predict the advantages that AMRs will provide and to decide how best to use them in order to maximize those advantages. The important technological advancements and decision-making areas for the planning and management of AMRs have been covered in depth in this literature review. AMRs have been defined, the literature has been organized and examined, and a planning and control framework has been suggested. Decision areas with applicable goals and methodologies have been selected based on the literature. In conclusion, there is still a dearth of study on many other intralogistics application areas since the majority of studies in this subject have concentrated on manufacturing and storage. Few studies have examined the circumstances in which decentralized control yields better performance or is more lucrative than centralized control. Simultaneously addressing several decision variables, like the number of vehicles, the locations of zoning and service points, or simultaneous scheduling and path planning, enhances comprehension of the interactions between various decisions and enables their evaluation to produce more balanced decisions. Because AI approaches may enable achieving many goals, they are particularly helpful for integrating decision domains. Even if research is expanding quickly, we come to the conclusion that certain areas of study have not gotten much attention, which leads to a research agenda for the future.

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