Review of Autonomous Mobile Robots for the Warehouse Environment

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Abstract

Autonomous mobile robots (AMRs) have been a rapidly expanding research topic for the past decade. Unlike their counterpart, the automated guided vehicle (AGV), AMRs can make decisions and do not need any previously installed infrastructure to navigate. Recent technological developments in hardware and software have made them more feasible, especially in warehouse environments. Traditionally, most wasted warehouse expenses come from the logistics of moving material from one point to another, and is exhaustive for humans to continuously walk those distances while carrying a load. Here, AMRs can help by working with humans to cut down the time and effort of these repetitive tasks, improving performance and reducing the fatigue of their human collaborators. This literature review covers the recent developments in AMR technology including hardware, robotic control, and system control. This paper also discusses examples of current AMR producers, their robots, and the software that is used to control them. We conclude with future research topics and where we see AMRs developing in the warehouse environment.

Keywords: Autonomous mobile robot, warehouse, smart manufacturing

1 Introduction

Autonomous mobile robots (AMRs) have been an active research field since the 1950s when the first Automated Guided Vehicle (AGV) was introduced [1]. Recently, with



Fig. 1 Human-robot collaboration in the warehouse [5]

the hardware advances in sensors and computing power, they have become more feasible. They have now been introduced into the manufacturing environment, particularly with logistics and material handling. In a traditional warehouse environment, goods are received on a truck and placed on a shelf. Then a team of pickers receives a list of orders that need to be filled for that day. An individual will then be assigned an order and then proceed to walk about the warehouse picking each item off a shelf and placing it in a container. Once the picker has finished the container will then be packaged, shipped, or knitted depending on the nature of the warehouse. Some companies modify this process and assign floor zones to individuals. Each person is responsible for picking items in their zone and bringing them to a sorting area.

Traditional warehouse structures suffer from motion waste, which is one of the 8 wastes in Lean manufacturing [2]. For companies to stay competitive, and lower logistic costs, many of them have turned to "smart warehouses", which deploy a series of tools to lower waste and increase production. Automated robots are used that either pick items or work with pickers to reduce the walking distance needed [see Fig. 1]. A good example of this is Amazon with their Kiva robots [see Fig. 2] [3]. Smart warehouses are not limited to robots, they also implement better planning strategies through warehouse management software (WMS), resource management, and path planning. Converting to smart warehousing does include some downsides. For example, the initial investment is high \$150 - \$200 per square foot but, the returns from reducing waste have shown to be substantial in the longer term [4].

In the manufacturing environment, robot-human interactions are becoming more important in daily operations. To help with efficiency, humans work alongside robots to pick up the shortcomings of each side. In warehouses, products of different sizes or shapes are handled from shelves and placed into bins. Robots have a particularly difficult time with this task since they are limited to the end effector installed as well as figuring out how to hold the object without it falling over. Human operators can easily do this task, but they are limited to fatigue after traveling back and forth across the warehouse. A solution would be to have the robot meet the picker at the product location and have the picker move the product off the shelf and onto the AMR. This paper specifically looks at this scenario and filters the search results based on their relevance.



Fig. 2 Amazon's Kiva robot [6]

Table 1 Reference Summary

	Subcategory	
Hardware	Sensors Processors Batteries	[7] - [21] [22] - [26] [27] - [31]
Robotic Control	Localization Artificial Intelligence Path Planning	[32] - [35] [36] - [39] [40] - [57]
System Control	Resource Management Scheduling Human-Robot Picking Methods Warehouse Flow and Layout Design	[58] - [68] [69] - [79] [80] - [84] [85] - [96]
Future Work		[97] - [107]

1.1 Review Methodology

This paper looks at the current state of AMRs that are being used in the warehouse environment. It includes not only research papers but also covers current AMR company hardware and the adjacent software. This paper used previous literature reviews, and research articles from IEEE Explore and Google Scholar. AMR-producing companies were found using a basic Google search. The starting keywords that were used were "AMR" and "warehouse". To narrow down the search results other keywords were used such as "scheduling," "decentralized," "AMR localization," "fleet size," "path planning," "battery management," ["AMR/AGV" + "hardware"], "zoning," "warehouse layout," and ["AMR/AGV" + "smart manufacturing"]. Combinations of the above keywords were also used to narrow down the search results. Papers were filtered from 2013 to 2024 with a few references to older papers. Table 1 summarizes the references used in this literature review.

This paper is organized as follows: Section 2 covers the recent AMR technological and software developments, Section 3 goes over robotic control through localization, path planning, and artificial intelligence (AI), Section 4 covers AMR system control by resource management, scheduling, human-robot picking methods, and warehouse flow and layout design, Section 5 goes over future research, and Section 6 is the conclusion.



Fig. 3 Sick TiM-S Safety Laser Scanner [13]

2 Hardware

2.1 Sensors

Typical AMRs are equipped with a wide variety of 2D and 3D cameras, accelerometers, gyroscopes, and Light Detection and Ranging (LiDAR). The data from these sensors are then brought together in a technique called sensor fusion to generate a map that the AMR can use to locate itself [7]. These sensors have become popular due to their speedy rendering and positional accuracy. Some popular 2D and 3D cameras are the Balser Dart series [8], Zivid M60 [9], and Nerian Ruby [10].

One of the most common sensors used in industry is LiDAR. The sensor works by sending out a known waveform into a scene, it is then reflected off of an object, and the LiDAR receiver captures a portion of the waveform and estimates the time it took, which distance is then derived from [11]. The sensors are very accurate and can have a working range of .05m to 25m [12]. Some LiDAR sensors rely on artificial landmarks, like reflective surfaces, already placed in the warehouse. These landmarks could become damaged, which could comprise the AMR's localization properties.

Table 2 describes a few AMRs used in the industry today. It shows the hardware that AMRs use as well as describes a few safety features. The SICK laser safety scanner is an example of an AMR safety feature [see Fig. 3]. The sensors have a scanning angle of 270° and a response time of 67ms [13]. Scanners like these are often combined with LiDAR to create an all-around safe robot.

Table 2 AMR Robots

	ADDVERB - Dynamo Series [14]	MiR - MiR Series [15]	Forward X - Max Series [16]	Locus Origin [17]	Locus Max [18]	Fetch - Roller Top [19]	Matthews AMR [20]	Bastian - ML2 [21]
Payload(kg) Speed(m/s)	100-1000 2	100 - 1350 1.5 - 1.5	600 - 1500	36	1361	80 1.5	70 1.8	200 1.8
Run Time(hr)	3.5-4	9.5 - 10	8	14	8-10	9	6-8	-
Accessorize	Yes	Yes	Yes	Multiple config.	No	No	Yes	Yes
Features	2D LiDAR, 3D Depth Cameras, Sensors for lower ground obstacle detection	2x SICK laser safety scanners, 2x 3D Depth Cameras, proximity sensors	2x LiDAR sensors, 2x 2D UWA Cameras, 2x 3D Depth Cameras, odometer, IMU	8 Sensors and Cameras	x2 LiDAR Sensors	2D Laser Sensor, x2 3D Camera,	LiDAR, x2 safety laser scanners	LiDAR, CAT 3 Safety system
	Positioning Accuracy(mm): +-20	Positioning Accuracy(mm): +-11	Positioning: Laser SLAM/ Visual Tag/ Visual Semantics	Tablet based UI, Integrated scanner	Autonomous charging during opportune times	Adjustable top deck height to reach conveyors	Can handle multiple totes and can include a roller conveyor attachment	Small size but many different configurations
	Fast Charging: 20-80% in 8min	Charging: 1.5 hrs - 50min for full charge, 1:6 - 1:12 charging to runtime ratio	Navigation: Natural/ Road Network/ Hybrid/Follow	Charge Time: 50min	Charge Time: 90min	Charge time: 3hrs for 90%	Navigation: Natural feature navigation from safety laser scanner input	Navigation: Natural feature

2.2 Processors

In order to handle a dynamic work environment, AMRs need to be able to take in data and process it in real-time. Coupled with the advancement of AI, the computational requirements have significantly increased [23]. However with the onset of new AI-specific CPUs, GPUs, and AI acceleration units like that of Jetson Xavier NX 16GB [see Fig. 4], Luxonis DepthAI [24], and Google's Coral Accelerator Module [25], AI computing has become more reasonable especially for edge computing [26]. These chips have also become essential to scheduling, especially in decentralized algorithms where each robot must make decisions and communicate messages in a short time frame.

2.3 Batteries

Batteries that have a high capacity and faster charging have made a significant impact on the robotics industry with most commercially available AMRs using lithium-ion batteries [27], [28]. Charge times like that of the MiR series of robots have a 1:6 charging to run-time ratio and can have a full charge in 50 minutes [15]. Charging mechanisms have also changed with the onset of wireless power transfer, allowing them to charge without a conventional connector [29]. With the onset of these batteries, resource management for battery consumption has become less of a hindrance to warehouse use of AMRs. However, for 24-hour operations, this still has to be taken into consideration. It is important to note that the environmental impact of lithium-ion batteries is still being debated. Currently, there is no method for recycling lithium-ion batteries besides incineration, which only extracts material that cannot be used to make more batteries [30, 31].

3 Robotic Control

3.1 Localization

Many of these robots are equipped with an array of sensors that help locate the robot such as 3D cameras, LiDAR, and encoders. Methods for localization vary from company to company but a common method is SLAM [32]. SLAM navigation uses features within the environment to build a map. The software gathers information from where the robot is and where it has been to build a probability distribution of all of the likely robot locations [33]. Another common localization method for warehouses



Fig. 4 NVIDIA Jetson Xavier NX Series[22]



Fig. 5 FowardX Max series of robots [16]

is hybrid navigation. This method uses sensor fusion from devices that can locate the robot in large and medium ranges like global positioning system (GPS) GPS (for outdoor environments) or ultrasonic sensors. Then when the robot needs to be located precisely, a short-range sensor (like a magnetic strip) is used to position the robot [34]. An example would be the Max series of robots from ForwardX Fig. 5. These AMRs have the capability to use SLAM, visual tag, or visual semantics for positioning [35].

3.2 Artificial Intelligence (AI)

AMRs are unique in that they operate in a dynamic environment. When there is an obstacle, the robot needs to be able to autonomously avoid or maneuver itself around the obstruction to continue its mission. Classification of obstacles is commonly done by using a visual system and machine learning. Neural networks, fuzzy logic, or recently deep reinforcement learning are then used to plan a path around the obstacle [36, 37]. Sensor fusion is also used when certain sensors become unreliable such as GPS when in a covered environment [38]. Without these techniques, AMRs would react to different obstacles in the same manor which becomes impractical when obstacles are consistently changing and moving [39]. This field of research is very active and continues to improve.

3.3 Path Planning

Path planning is used to plan a trajectory from the current position of the robot to the target using the extracted information from the environment. This problem is typically approached either with a static or dynamic environment. In the warehouse, there are many moving objects like personnel, forklifts, or other autonomous vehicles [40].

For obstacle avoidance, bug algorithms are a common approach to path planning. In general, once an obstacle is detected, the robot will move around the object until it finds the path back to the target objective. Many variations of the bug algorithm exist like that of TangentBug, which finds the shortest path based on a local tangent graph from range data [41]. Vector field histograms (VFH) are also a common obstacle avoidance algorithm. In this, a robot detects an obstacle and builds a cell histogram

based on the range data. That cell histogram is then converted to a polar histogram where valleys are detected and a path is chosen while taking into consideration the size of the robot [42]. A variation of the VFH is the VFH* algorithm which uses A* search to build a tree of candidate directions [43]. Another common approach are artificial potential fields [44]. In this, calculated forces are generated for the target and obstacles. When the vehicle moves closer to a obstacle, a repulsive force is acted upon the vehicle avoiding the obstacle while an attractive force from the target keeps the vehicle moving towards the goal. Dang and La [45], extend the artificial potential field by incorporating a rotational force field and a repulsive force field. This new combination helps move a vehicles around complex obstacle shapes were it would otherwise get stuck.

Heuristic algorithms for path planning have recently been a popular research subject. Examples include neural networks, fuzzy logic, genetic algorithms, and particle swarm optimization. Genetic algorithms [46] iterate through potential solutions and find the best selection. This selection is then used to build more solutions and eventually find the optimal path taking advantage of operators like mutation, crossover, and selection [47]. A hybrid adaptive genetic algorithm is proposed in Zhou et al. [48]. The paper addresses the issue of preventing a local optimum by initially performing genetic operations with fixed parameters and then applying adaptive genetic operations. The algorithm adjusts the crossover and mutation probability in sinusoidal adaptive transformation. Fuzzy logic uses the concept of True and False (1 or 0) but extends it to include more freedom between states. First introduced in 1965 by Zadeh [49], fuzzy logic algorithms have now advanced to include hybrid path planning like that of Hassanzadeh and Sadigh. [50] or using fuzzy logic with ant colony optimization Song et al. [51]. In Song et al., the robots were able to find an optimal path by not only considering the shortest length but factors like the least number of intersections, least traffic, and safety. In another paper by Young and La [52], they combine consensus, cooperative learning, and flocking. In this, a multi agent system is used to first group together the many different actors. Then the algorithm is trained via reinforcement learning to avoid obstacles. Lastly, to figure out where a moving obstacle is coming from, a consensus algorithm [53] is used. This allows the multi agent system to move as group to avoid oncoming obstacles.

Often, path planning for a single robot is not the most optimal, especially in a warehouse setting where there could be hundreds of robots. Factors like traffic congestion can slow the entire system if not considered. A genetic multi-robot path planning (GMPP) algorithm was proposed in Fan et al. [54]. To avoid collisions with obstacles or other robots the authors integrated a collision detection and elimination mechanism. The collision mechanism calculates where robots will collide then a central planner decides which robots have priority by a random dynamic priority policy. In a recent paper Pradhan et al. [55], the authors were able to coordinate multi-robot navigation by having a particle swarm optimization algorithm train a feed-forward neural network. They simulated the results in a dynamic environment and compared them to a traditional potential field method [44]. A hybrid approach using a convolutional neural network and a graph neural network was proposed in Li et al. [56]. Their approach focuses on decentralizing the multi-robot path planning problem. In

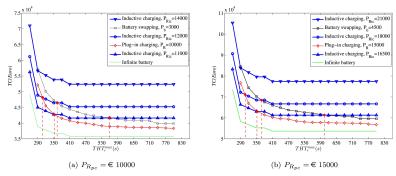


Fig. 6 Robot battery cost comparison. TC(Euro): Total cost, $THT_r^{max}(s)$: Required system throughput time, $P_{R_{pc}}$: Plug-in charge robot price [59]

Chen et al. [57], the authors propose a decentralized multi-agent collision avoidance algorithm based on deep reinforcement learning. The approach takes online predicting data for interaction patterns and offloads it to an offline learning procedure. Through this, a robot can predict the behavior of its neighbors even when those neighbors are non-communicative.

4 System Control

4.1 Resource Management

4.1.1 Battery Use

In a warehouse environment, demand often fluctuates. Sometimes orders will surge and strain the available resources within the warehouse. Often bottlenecks are created when there are not enough staff to handle these fluctuations. This can lead to increased lead time for customers, which is undesirable in a very competitive market where ontime delivery is a selling point [58]. For a multi-robot system, this must be taken into consideration. Companies like that of ADDVERB [14] and their AMR called Dynamo, take advantage of lows in demand by using that time to send robots to charge. This helps maximize the robot's utilization and energy management.

Traditionally, battery management is usually handled by a rule-based policy. Whenever the battery is low the robot will head to the charging station regardless of where the robot is, demand, or current schedule. This can lead to issues where too many robots charge while there is a surge in demand. Zou et al. [59] compared battery swapping, inductive, and plug-in charging techniques. They showed that inductive charging has the best throughput time and that battery swapping outperforms plug-in charging. Fig. 6 shows the comparison of the three strategies at different robot price points. Mu et al. [60] propose a method that models battery management into a Markov Decision Process and then uses a deep reinforcement learning algorithm to solve it. Their results show that their method outperforms standard rule-based strategies by 5% in fulfillment rate and has significantly fewer backlogged orders after a long period of time. In another paper De Ryck et al. [61], the authors use a decentralized approach based on an extension of the traveling salesman problem. Their focus was

based on when to charge and how long. Their algorithm also allows the robot to be charged along its current operation trajectory.

4.1.2 Fleet Size

Determining the correct number of AMRs to use on the floor is important to maintain a consistent lead time. Areas on the warehouse floor where there is a lot of demand can turn into a bottleneck if there are many robots or personnel in the area. Likewise, if there are too few robots, shipments will be paused while orders are being fulfilled. An example of how companies handle this problem is the MiRFleet Software from MiR [62]. This software can handle up to 100 robots with different modules and can coordinate traffic control in critical zones. It allows the user with a basic level of programming to help manage the fleet's priorities. Once the setup and programming are completed, it carries out operations based on the position and availability of the robot.

In literature, the fleet size problem can be solved by queuing theory, linear and integer programming, or discrete and continuous event simulation [64]. In a paper by Chaikovskaia et al. [63], the authors, using integer linear programming, considered a fleet under a homogeneous system with robots that can cooperate with each other to carry a load. The paper uses different scenarios where cooperation is inefficient vs. when it is optimal when carrying a load. Fig. 7 shows an example of how p and m-bots work together to carry a load, the p-bot being composed of two m-bots. A modified memetic particle swarm optimization (MMPSO) algorithm was proposed in Chawla et al. [65]. They first estimated the fleet size by a analytical model and then optimized it using a MMPSO algorithm. They tested with three different floor layouts and compared MMPSO to the analytical model. Vivaldini et al. [66], created a task assignment module that estimates the number of AGVs based on the ratio of defined execution time and total time spent routing. Most articles deal with homogeneous systems with a fleet of the same robot. Rjeb et al. [67] proposed a method to tackle fleet sizing of a heterogeneous system by an integer linear program. In a 2024 paper by Maurizio et al. [68], the authors propose a genetic algorithm and a mixed-integer linear program to tackle a multi-objective problem consisting of figuring out the best schedule for minimizing makespan and the number of AGVs that are under battery constraints. They compare their results to actual data that was used in a manufacturing facility.

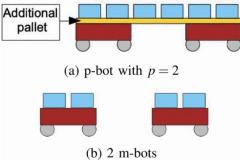


Fig. 7 Robot cooperation with p and m-bots [63]

The genetic algorithm was shown to outperform the solution that the manufacturing facility was currently implementing.



Fig. 8 Fleet management system from ADDVERB [69]

4.2 Scheduling

In academia, a large amount of research has gone into the decision-making process in scheduling orders. Traditionally, these systems are centralized and use hierarchical control. However, with the advancement of computational power, AI has played more of a role in task scheduling in a manufacturing environment [39]. In industry, scheduling is handled by a warehouse management system (WMS). This software allows administrators to control the daily warehouse operations from the time goods enter to when they move out [70]. A common example of a WMS software is SAP [71]. One of the benefits of using a WMS is that work orders are only given when there is enough inventory to fulfill them. Often this software controls inventory at a high level leaving the planning of how orders are physically picked to lower-level software. ADDVERB Fleet Management System is an example of this lower-level control [69]. It handles the task allocation along with the navigation of each robot. Fig. 8 shows what this software controls and how the user and robot integrate with each other. The traditional approach to scheduling handles task assignment as a path planning problem, assuming the AGV/AMR plans the path from the current location to the target. These algorithms are limited by their flexibility since they do not consider a dynamic work environment.

Scheduling problems are considered to be NP-hard problems [72]. Due to the complexity, they are normally solved through heuristic algorithms like genetic algorithms, particle swarm optimization, or reinforcement learning. Yokota [73] proposed an algorithm that uses a min-max strategy to coordinate between robots and humans. The algorithm centers around the co-involvement of robots and humans with the humans picking an item off the shelf and placing it onto an AGV. Each AGV is equipped with

a balanced workload based on minimizing the total travel path. Then a heuristic algorithm, with two different rules, is then used to match a picker with a robot. In Yu et al. [74], a algorithm is proposed using a two-stage heuristic algorithm. The first stage uses clustering to divide packages based on similarity and group them together with the idea that a multi-load AGV can sort the packages of one group in one operation. Then in the second stage, a load-balancing scheduling algorithm assigns and sorts each of the groups to the AGVs. A hierarchical soft actor-critic algorithm is proposed in Tang et al. [75]. Hierarchical reinforcement learning algorithms attempt to reduce the computational complexity of a dynamic environment by layering learning strategies. Soft Actor-Critic (SAC) algorithms are more practical in robot control since they are able to solve both discrete and continuous problems. The algorithm centrally assign tasks to the AGVs then the robots collaborate in planning the actual path. In another paper Li and Wu [76], proposed a Genetic Algorithm Considering Genome, which takes into account dynamic task scheduling as well as determining the charging schedule. It is able to iterate through a genome, which is composed of several neighborhood solutions. Their algorithm can quickly find a local optimal solution and, in a later stage, explore the neighborhood of the the local optimal solution using internal cross and mutation. In a 2024 paper, Li and Huang [77] propose a scheduling algorithm for heterogeneous AGVs. This allows for the use of several different kinds of AGVs performing different tasks. They were able to implement several different algorithms including Fist Come First Assign, Heterogeneous Task Assignment, and Optimization Assignment and compare them to past works.

Few studies have been conducted that offer a way to decentralize scheduling. Hierarchical control often finds the optimal solution but suffers from a lack of robustness or flexibility. If the central control unit goes down the entire system cannot operate. Decentralized control has the advantage of scalability and the ability to continue operation even if one unit fails. Basile et al. [78], used a version of an auction-based approach called the sealed-bid method in which an agent cannot see other agents' bids. Any robot can play the role of auctioneer and takes bids in from other robots acting as an agent. The auctioneer selects the best bid based on the time it takes to complete a mission. In another paper by Warita and Fujita [79], the authors set up a multi-agent decentralized algorithm using a fully decoupled upper confidence tree (FDUCT). The idea being that each AGV will use FDUCT to plan its own actions while predicting the actions of other agents. They also implement an item-exchange strategy to help balance the load of each AGV and avoid idle time.

4.3 Human-Robot Picking Methods

4.3.1 Picking Methods

Picking is defined as the process of scheduling customers' orders, assigning stock, releasing orders, picking items off of storage locations, and disposal. The majority of warehouses that employ humans deploy a picker-to-parts system, which involves the picker walking or driving to pick items. More automated warehouses will use a parts-to-picker method where shelving robot units or cranes move products to the picker[see Fig: 9]. Within picker-to-parts systems, there are several variants like batch picking

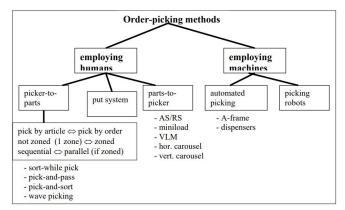


Fig. 9 Traditional picking methods [80]

or zoning. Batch picking has the picker pick multiple orders at once then sorted in a later sequence. Zoning is a system in which the warehouse floor is divided into areas where humans pick items that are only in their designated area [80, 81].

4.3.2 Human-Robot Collaboration

In AMR-assisted picking, the laborious task of traveling with a picked item is reduced by the use of a robot. In a paper by Srinivas and Yu [82], a collaborative humanrobot order-picking system (CHR-OPS) was presented with the goal of minimizing the tardiness in their batch order system. Three sub-problems were made to optimize; the number of items picked in one tour, batch assignment and sequencing, and pickerrobot routing. Their results emphasized the impact of AMR cart capacity, AMR speed, and human-robot team composition. In another picker-to-parts system, Zulj Ivan etal. [83] used zoning to have humans pick batched items and drop them off in pick location for that zone. A robot would then collect and transport the batched items to a depot where they will be sorted. Their approach focuses on minimizing the tardiness of all customer orders. The algorithm used a two-stage heuristic of adaptive large neighborhood search (ALNS) for batching and NEH heuristic for the sequencing the batches. Zhao et al. [84] proposed a human-robot collaboration algorithm in a partsto-picker system. Their algorithm uses an adaptive large neighborhood search method that is embedded in a tabu search algorithm. They compare their algorithm with others and show it effectiveness at lowering makespan.

4.4 Warehouse Flow and Layout Design

Traditionally, warehouse layouts can be classified as a conventional, non-conventional, and general warehouse. Conventional warehouses are those with a rectangular shape and parallel aisles that are perpendicular to straight cross aisles. Layouts with two cross aisles are considered as single-block warehouses. Fig. 10 shows a two-block layout with three cross aisles. Non-conventional warehouses arrange their aisles in a manner that allows easier access to certain areas of the warehouse [see Fig. 11]. For example, fishbone warehouse layouts offer a scheme that is shown to reduce travel distance by

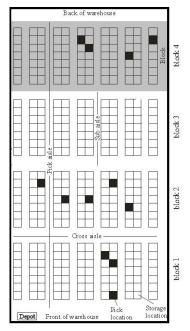


Fig. 10 Conventional warehouse layout [90]

10-15% when compared to conventional warehouses [85]. General warehouses do not make any assumptions about the aisle locations. Rather, they are modeled after general distance matrices [86]. The layout also defines aisle characteristics. For a multi-robot system, wide aisles are a benefit since they allow room for robots to move around. However, narrow aisles reduce the distance traveled for items that are picked on either side of the aisle. Items that are picked low to the ground and do require any vertical tools to grab are considered low-level [87–89]

In a paper by Hamzeei et al. [92], they investigated the bidirectional topology of a block layout design of a warehouse floor and the locations of delivery and pickup stations. They developed two algorithms; one used a cutting-plane algorithm, and the other used simulated annealing to solve the problem heuristically. Li and Li [93] looked at optimizing a multi-row layout of a machining workshop while considering AGV path flow. The multi-row layout consists of robots covering an area that has multiple rows and can be picked on either side [see Fig. 12]. The proposed algorithm uses a hybrid method between non-dominated sorting genetic algorithm-II and tabu search. By focusing on the AGV path they were able to lower the material handling cost of the facility [94]. In a 2023 paper by Zhang et al. [95], the authors consider the case of a fully automated warehouse with no human personal. Since robots do not need a structured layout to locate parts, the authors make the case that an optimized layout, that does not resemble a human-designed layout, can be used to increase throughput. The layouts that are generated from their algorithm are non-traditional and do not have column-row aisles in a typical warehouse layout. To determine the storage location of items Bao et al. [96], classified items based on their profit or throughput rate. Products

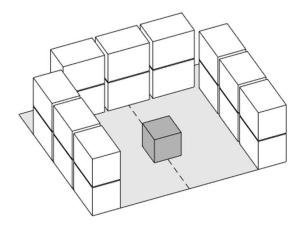


Fig. 11 Non-conventional U-shaped warehouse layout [91]

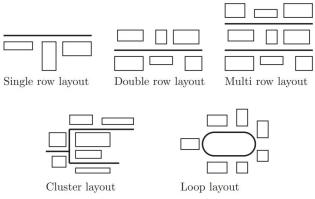


Fig. 12 Classifications of row layout [94]

that are labeled as "A" would be placed closest to the output gate to reduce travel time.

5 Future Work

Scheduling has normally been focused on a centralized network of robots. However, this creates a dependency on the central unit and demands one unit to do most of the computational work. Decentralizing this task could prove to be more flexible and scalable. The papers presented [73–76] simulate 3 to 10 robots at a time. In real-world applications, warehouses could deploy hundreds [97]. Only a few studies were found that deal with decentralized scheduling [78], [98].

Warehouse zoning is important for dividing the workload on the warehouse floor. For AMR networks this means faster response time and less likelihood of congestion.

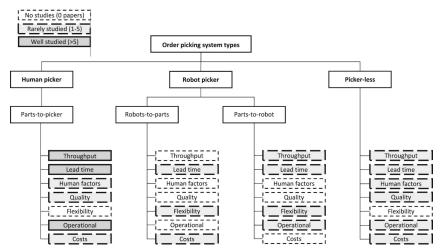


Fig. 13 Areas of focus within part-to-picker systems [107]

Most of the studies presented [92–94, 96, 99–106] focus on AGV vehicles. One of the downsides of using AGVs, are the pre-planned routes they must follow. AMRs do have to deal with this issue since they can find alternate routes around obstacles or other robots without the need of a user designing an optimal path. More research needs to be done into modeling dynamic zones for AMRs to balance workloads and ensure a rapid response.

Many papers use performance indicators like lead time, tardiness, distance traveled, and operational efficiency to measure how well their algorithm works when compared to others. However, in human/robot collaborative spaces, human factors are rarely considered. In another literature review that looked at parts-to-picker systems, Jaghbeer et al. [107] highlighted that human factors are rarely focused on in picker-less, robot-to-parts, or parts-to-robot OPSs (order picking systems) [see Fig: 13].

6 Conclusion

Autonomous mobile robots (AMRs) have made a significant contribution to manufacturing specifically in warehousing improving performance and productivity. Several technological developments in localization, sensors, and battery management have AMRs more feasible to be deployed. AI techniques have also played an important role in the decision-making of AMRs. Genetic algorithms, deep reinforcement learning, and neural networks have reduced the complexity of scheduling paving the way for decentralization. Different warehouse layouts, picking strategies, and human-robot routing strategies have helped in the development of human-robot collaboration. With this research, AMRs have shared the workload of laborious and repetitive tasks allowing humans to be less fatigued and focused. Though most of the research that has been presented in this paper has focused on warehousing, not enough has been done studying applications in other environments such as outdoor warehousing of docking yards

or hazardous areas. It is concluded that the research in this field is growing rapidly and is currently changing the manufacturing industry.

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