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Bridging the Gap in Warehouse Automation: A Comparative Analysis of Autonomous Case-handling Mobile Robots (ACMRs), AMRs, and AGVs

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Abstract

With automation in the warehouse getting increasingly common, much of the literature focuses either on Automated Guided Vehicles (AGV) or Autonomous Mobile Robot (AMR), leaving quite a gaping hole in the body of literature related to Autonomous case-handling mobile robot (ACMR). The ACMR offers the flexibility of AMRs but adds the precision of case handling and, therefore, is especially fit for the demands of addressing the challenges of high-throughput environments: dynamic layouts, congestion, and the demands put on rapid, accurate order fulfillment. However, most of their potentials are yet unexplored, especially in cost efficiency, scalability, and operation performance. This thesis tends to fill in that gap by presenting, in the IBM CPLEX optimization tool, a mathematical model for the optimum deployment of ACMR at minimum operational cost with maximum throughput. Further scaling of the model is covered by using realistic scaled simulation friendly empirical data obtained by leading robot manufacturers such as Hai Robotics, Invia, and Quicktron. The model will be further validated through simulations, which can allow ACMR to benchmark with AGVs and AMRs based on key indicators such as cost efficiency, distance travelled, and speed of completion of order. In the light of the above, the present study evidences the benefits of ACMR in trading up the deficiencies of the traditional automation technologies. The results will imply practices to be followed by the warehouse operators and will form a basis for further academic investigation with regard to ACMR technologies, their integration, and their transformational potential within automated warehousing.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background & Context

E-commerce, growing rapidly in recent times, has completely redesigned the whole concept of the logistics and warehousing industries. The global move toward online shopping, stimulated by the rapid advance in technology and change in consumer behavior, places pressure like never before on warehouses for efficiency with flexibility in their operations. According to industry reports, Amazon's strategic deployment of robotics in its fulfillment centers led to a 20% reduction in operating expenses, saving approximately $22 million annually per fulfillment center [1]. This surge has increased order volumes and shrunk delivery windows; thus, a major overhaul in warehouse operations is required to organize the processes optimally, reducing cycle times and increasing throughput at high accuracy with minimum costs [2].

Traditional warehouses, which have long relied on human labor to carry out activities such as order picking, sorting, and inventory control, are struggling to keep up with heightened demand-particularly large sales events such as Black Friday and the holiday season-which further exacerbates this problem [3]. Labor shortages and increasing labor costs have, however, forced companies to adopt the automation of warehouse operations in order to enhance efficiency and scale. The implementation of Robotic Mobile Fulfillment Systems (RMFS) demonstrated higher throughput with a reduction in cycle time by effectively utilizing the availability of robots and reducing manual labor dependence [4].

Automatic system development, primarily within the organized warehouses, has facilitated business operations in terms of better utilization of resources with minimized manual intervention [5]. They may be less effective, however, in fluid, unstructured situations that call for flexibility.

In this context, Automated Guided Vehicle robot shuttles (AGV), which work on fixed paths using magnetic tracks or any other predefined guidance system, dominated the first wave of automation in the industrial sector. These systems are reliable but less adaptive to the changes in the warehouse layout and often need substantial time for their reconfiguration [6]. AGVs work well in fixed structure environments, but by the nature of the structure, they tend to be inflexible. Most such systems run on pre-built routes, from which modification to these networks might become difficult sans exhaustive restructuring. [7] considered increased dynamics within the warehouse, such as continuous changes to the layout due to different mixes and volumes of orders, very serious problems of scalability and flexibility in AGV robot shuttles will arise. This attribute is due to the usage of navigation on fixed routes and to the imposition of a central unit constituting an important obstacle in adaptability to real-time changes [8].

AGV robots work well in structured warehouse environments; however, their inability to make more precise changes easily due to reliance on pre-programmed routes makes them less adaptable in dynamic situations [9]. Because of such limitations, the need for developing Autonomous Mobile Robot (AMR) shuttles arose. AMR shuttles are huge improvements in that they utilize advanced sensors and AI algorithms that allow them to move independently, with no fixed paths, adapting even to sudden changes in their environment. The machines will auto-optimize the travel routes in order to avoid obstacles and adapt to new layouts. It is most useful in complex warehouse areas. This would further enable them to perform route optimization, avoid obstacles, and adapt to new layouts, hence suitable in a complex warehouse environment. According to [9], AMRs use different kinds of sensors and cameras that make them detect obstacles such as crowds and fallen boxes unexpectedly, after which they will make a detour to pass around them independently to make sure they do not get out of their mission.

Despite their flexibility, AMR shuttles also face difficulties in high-density environments. In the settings where fastidious case management is required to meet an expanding need for rapid and accurate order fulfillment, both congestion and coordination challenges can critically hinder operations. In turn, this creates delays in the execution of tasks, inflates operating costs, and reduces throughput, especially in the dynamic warehouses that rely upon high throughputs. [10]. Automated Case-handling Mobile Robot shuttle (ACMR) is a giant leap in developing technologies, putting together flexibilities of AMR shuttles with distinct case-handling capabilities. They do exceptionally well in high-throughput conditions whereby much attention is needed in terms of precision, speed, and accuracy; hence, solving problems that the AMR shuttles go through in a highly congested warehouse environment.

It's now becoming a go-to solution to fill the gaps in warehouse automation: ACMR combine the flexibility of AMR shuttles with specific case-handling capabilities. While the usual avatar of AMR shuttles uses only the movement of goods from one station to another, the ACMR shuttles are designed to pick up the cases from the shelves and move them to packing areas with a very high degree of precision. By doing so, ACMRs can drastically reduce order cycle times and throughput, hence making them desirable to have in high-throughput settings such as e-commerce warehouses where speed and accuracy are a big deal. Because ACMRs can handle cases directly, it enhances operational efficiency since minimal dependency on manual labor is involved, thus speeding up the process of fulfilling orders. Despite their possible benefits, ACMRs remain comparatively overlooked within scholarly investigations, emphasizing a void that this thesis intends to fill by assessing their influence on the efficiency of warehouses and the reduction of costs.

Evidence of how automated warehouse handling by Kiva robots especially has been given by Amazon and other huge e-commerce companies. In regard to the next phase for automation of warehouses, the use of such increasingly specialized robots has been realized. Combining the flexibility of AMRs with case-handling abilities necessary for high-precision, high-throughput operations, ACMRs can be set up to be extremely good solutions to satisfy modern warehouse demands. By taking advantage of advances in robotics, warehouses can have similar efficiencies, especially in environments where rapid order fulfillment and high handling precision are required.

Given the fact that ACMRs can provide such added benefits in introducing case-handling to the flexibility of AMRs, they are still barely mentioned within a scientific context. No in-depth analysis in the literature on cost-effectiveness, scalability, and impacts on general operations has been reported; thus, these topics need further investigation. In other words, AGVs and AMRs were outstanding innovations for the automation of warehouses, but ACMRs really signal the start of a new generation. With higher flexibility, accuracy, and scalability, they can easily help modern e-commerce warehouses overcome such challenges. Despite promising capability, few works have been conducted to study cost efficiency, scalability, and operational performance of ACMRs. The present thesis aims at contributing toward such gaps, proposing a data-driven mathematical model for assessing the deployment of ACMRs, with special consideration of the problems of minimizing operational cost, improving throughput, and enhancing adaptability.

1.2 Problem Statement & Research Gap

Conventionally, an AGV shuttle has been engineered to navigate along specific trajectories, making them proficient in specific regulated settings but considerably constraining their functionality in fluctuating warehouse conditions. Recent studies have shown that AGV shuttles face difficulties in adapting to an obstruction along its specific route because an AGV is naturally incapable of swiftly and efficiently rerouting autonomously without human operator intervention [11]. This is very important, especially in environments with changes in layout very often or with obstacles that suddenly pop up.

While contrary to expectations, such challenges have given rise to the development of AMR shuttles. Unlike the AGVs, the AMRs rely on a powerful set of sensors like Light Detection and Ranging (LiDAR) combined with AI-driven algorithms for their navigational autonomy through unstructured environments. It implements real-time route optimization with advanced path planning and obstacle avoidance [9].Whereas the AMR shuttles make use of a series of sophisticated sensors, artificial intelligence algorithms, and self-directing navigation systems that offer far more flexibility. [12] and [13] mentioned that AMRs can map their environment, perform path planning, and dynamically respond to changes by avoiding obstacles without remote control. Whereas AMRs are very capable of making decentralized decisions while avoiding obstacles, they still normally lack the precision in high-density case handling, particularly where there is a need for rapid picking and sorting as instituted by [14].

In addition, this may lead to more picking errors, poor capacity utilization, and higher operating costs in large-scale e-commerce fulfillment centers that continue to increase consumer expectations. According to [15], improvements in pick routes are necessary to reduce travel times and operational failure related to the routes. Improvements are essential in maintaining efficiency in dynamic and fast-moving environments such as e-commerce.

AGVs are very common in improving transportation efficiency and routing in material handling systems. However, being rigid, it is less well adapted in a dynamic environment where frequent changes in product mix occur along with constantly fluctuating consumer demand. In fact, researches proved that performance evaluation of material handling system (MHS) has been problematic due to issues relating to variability of demand, product mix changes, and time-dependent environments, adding more complexity to the optimization processes of such systems [16].

ACMR shuttles are those that represent a merger of navigation capabilities for AMR shuttle with case-handling mechanisms. They can be made very effective in case-level picking, sorting, and handling, hence quite suitable for very high-throughput environments where precision and speed are at a premium. Despite huge potential, there is a huge gap in the literature, since there is no study direcyty or indirectly compared the cost efficiency, scalability, and performance of ACMRs against the AGVs and AMRs. Much of the current research focuses on how to optimize AGVs and AMRs and has totally overlooked the benefits which can be realized with ACMRs.Specific research gaps like these are bridged by this thesis, which develops a data-driven mathematical model for the optimization of ACMR deployment, focusing on the minimization of total operational costs while increasing throughput efficiency. Besides that, controlled simulations will be conducted using small scaled simulation friended real-world data from leading robot manufacturers in comparing ACMRs' performance against AGVs and AMRs. The quantification of these metrics, such as cost savings can be used to show how ACMRs improve efficiency and scalability while reducing labor costs in warehouses. This paper thus bridges an important gap in both the academic and practical understanding of strategic deployment matters concerning ACMR shuttles within automated warehouse settings.

1.3 Research Objectives

The general objective of the research is to improve warehouse operations by exploring cost-effectiveness and efficiency when using different shuttle systems, ACMRs over AGVs and AMRs. On this premise, the framework of a mathematical model using actual small scaled simulation applicable data, which is obtained directly from the robot manufacturers themselves such as Hai robotics, Invia, Quicktron robotics, will be developed in order to pursue minimum total cost of operation in warehouses. The findings will also be practically relevant and applicable in any real industrial context by leveraging accurate performance metrics. The specific objectives of this thesis are:

- Minimize the total cost of warehouse operations by developing 3 mathematical model using Python environment with usage of IBM CPLEX, considering factors such as, energy consumption, task allocation, and travel efficiency
- Collect empirical data from well-recognized robot manufacturers, such as Hai Robotics, Invia, and Quicktron, and scaled that data to use simulation to fine-tune the model to make it more precise and with better relevance in prediction.
- Simulation tasks of ACMR shuttle, AGV shuttle, and AMR shuttle shall be done in Python environment with the help of Pyomo library, over the mentioned key indicators, namely cost reduction, throughput, and adaptiveness in dynamic environments.

1.4 Significance of the Study

As it is, the research contributes theoretically and practically to the field of logistics and warehouse automation, which is much needed in addressing the subject matter. While AGV shuttles and AMR shuttles have been the focus of plenty of research work, the literature is scarce on ACMRs. Research mostly lacks specifics on how ACMRs fare against AGV and AMR in terms of cost efficiency, operational flexibility, and productivity. The thesis captures this void by formulating a real-world, data-driven model, from specifications of actual robot manufacturers, to measure ACMR's performance in warehouse environments.

In theory, this research expands the existing body of knowledge by presenting a comparative framework that positions the strengths and limitations of ACMRs concerning other robotic solutions. This study holds the particular advantage of formulating a mathematical optimization model that systematically derives an analytical context for estimating cost savings and efficiency improvements realizable through ACMR deployment, as well as AGV and AMR. The framework integrates critical decision variables such as task scheduling, navigation strategies, and energy management for insights into ACMR's performance under real-world constraints in warehouses.

From a practical perspective, this research offers a guide for logistics managers and other practitioners considering investment in warehouse automation. Likewise, this study provides data-founded insights regarding task execution time, energy usage, and cost effectiveness by quantifying operational trade-off realities between ACMRs, AGVs, and

AMRs. ACMRs provide specialized benefits for optimizing warehousing, given their multi-case retrieval capabilities and adaptability in high-density storage, and this research makes practice-specific suggestions about their scalability and deployment.

This research creates an important basis for subsequent studies on introducing ACMRs into warehouse systems. It gives a model-based and optimization-driven approach for systematic evaluation of robot-assisted material handling operations. Given the model's focus on real-world inspired operational constraints and decision-making variables, it provides a scalable framework for assessing efficiency in warehouses based on different robotics systems' performance.

Thus, this research also fulfills a critical void in academia because systematic comparisons of ACMRs with AGVs and AMRs have been few and far between; it also contains practical recommendations for industry actors. The data-driven approach, combined with mathematical optimization techniques, has improved understanding of ACMR capabilities vis-a-vis their evolving role in next-generation warehouse automation.

1.5 Overview of Methodology

This study adopted a quantitative research approach, which has incorporated mathematical modeling and simulation in Python and thereby comparative analysis meets this objective. The study has focused on the formulation of mathematical optimization for deployment of ACMR shuttle as well as AGV shuttle and AMR shuttle in a warehouse environment. The model would optimize the overall operational cost, increase allocation efficiency, and maximize throughput while considering all practical restrictions in relation to the energy consumption, scheduling of tasks to complete, and navigation strategies of the robots.

Thus, IBM CPLEX was used as the main big mathematical modeling tool, which is very effective for such large-scale optimization problems since CPLEX can formulate and solve a cost-minimization model that integrates task assignment, energy constraints, and robot movement dynamics. This model is valid in the real sense as it will take data from leading robot manufacturers such as Hai Robotics, Invia and Quicktron. Adoption of the real specifications and performance parameters brings the model to reflect realistic warehouse scenarios as applicable to the industry operations.

After the mathematical optimization phase, the study runs several warehouse operation scenarios in Python simulation to validate the model further. The simulation framework captures the performance of ACMRs in comparison to AGVs and AMRs under various operational conditions. These specific conditions include Key Performance Indicators (KPI)s reflecting cost efficiency, total distance traveled, task completion time, and energy consumption, which are the primary comparative metrics. [5] and [17] had previously investigated this aspect, highlighting these KPIs' importance in the comparative effectiveness evaluation of robotic systems in wholesale warehouse optimization.

As defined by [18], the performance assessment of warehouse systems is based on multiple criteria as here follows: Cost aspects (investment and operational costs), Service (is order fulfillment accurately and timely), Order lead time (time between order placed and order completed), Flexibility (ability to cope with variations in parameters of the process), and Scalability (ability to deal with increasing demand and load on the system). Integration of mathematical modeling and simulation makes it possible to study much beyond just comparisons among ACMRs, AGVs, and AMRs; it makes the results theoretically and practically sound. It's noted to be effective, when validating theoretical optimization processes, using real-world performance data [19]. Also, simulation-based validation improves system throughput, scalability, and cost efficiency at the robotic level [20]. Changes in which this study will come are action-oriented for logistics managers and industry professionals toward efficient operation optimization.

1.6 Structure of the Thesis

This thesis is organized in the following manner to achieve comprehensive coverage of the research objectives and questions:

- Chapter 1- Introduction: This chapter introduces the background, problem statement, research objectives, and the significance of the study in setting up a basis for the thesis.
- Chapter 2- Literature Review: Literature Review: This section of the paper reviews the state-of-the-art research done in the area of warehouse automation and points to strengths and weaknesses in existing research on AGVs, AMRs, and ACMRs. This identifies the gaps in the current research, particularly the lack of research relative to ACMRs.
- Chapter 3- Mathematical Model: In this chapter, the mathematical optimization model for task allocation, energy management, and general operational efficiency

in a warehouse environment is developed. The model is formulated with the use of IBM CPLEX in the Python environment, with real-world specifications being taken from the manufacturers of robots like Hai Robotics, Invia, Quicktron. The assumptions, constraints, and the important decision variables in the model will also be discussed in the chapter.

- Chapter 4- Case Study & Results: This chapter will be providing a proof-of-concept exercise via simulations of the mathematics-based techniques using Python. This chapter includes the ACMR shuttle comparison with other systems like AMR shuttle and AGV shuttle based on performance indicators such as total operational time, energy consumption and travel distance.

- Chapter 5- Conclusion & Future Works: The final chapter highlights the key findings of the study

2

Literature Review

2.1 Introduction to the Literature Review

2.1.1 Purpose of the Literature Review

This literature review outlines the historical evolution and current state of warehouse automation—from early AGV shuttles to AMR shuttles and the latest ACMR shuttles. The review synthesizes the strengths and weaknesses of each system and identifies key research gaps in control strategies, load capacities, and system integration. Given that order picking operations account for approximately 65% of warehouse operating expenses and 60% of labor activities [21], innovative automation solutions are essential to reduce costs while maintaining or improving operational efficiency.

2.1.2 Background: Reason for Automation in Modern Warehouses

E-commerce's enormous development along with the compounding complexity of inventory management has pushed warehouses to all-time highs. Manual order picking, which used to get by in small-scale operations, is now suffering enormously under the strain of high biased volume and a complex configuration, so no doubt it will end in huge error and inefficiency [5]. The first automation moves were made by introducing in 1955 AGV shuttles to perform repetitive transport tasks and reduce labor [22]. [23] described AGVs typed shuttles as critical when it comes to moving materials within defined areas, especially structured warehouse settings where they drive along magnetic or painted paths. Unfortunately, their dependency on paths makes them inflexible; large-scale layout changes often require wholesale route restructuring, hitting their appropriateness for dynamic slotting to "chaotic storage" warehouses, where picking and delivery paths are constantly changing.

2.1.3 Scope of the Review: 3 Major Shuttle Types & Optimization Strategies

This review focuses on three major automation technologies and optimization strategies for multi-robot warehouse systems:

- **AGV:** Built to perform repetitive lifting and transporting tasks in highly structured environments, following fixed routes with help of magnetic tracks, laser sensors, or RFID tags [24]. Their continuous distribution is perfectly suited to environments, such as automotive assembly lines and large distribution centers, where the layouts are stable and less reconfiguration will be required [6].However, centralized control and fixed systems make it difficult for warehouses to adapt when their layout changes, limiting their ability to grow and adjust to new demands. [25]
- **AMR:** AMRs have been installed formidably to provide solutions to the limitations of AGVs, utilizing modern sensors (such as LiDAR and 3D cameras) in conjunction with artificial intelligence algorithms and SLAM for autonomous navigation in dynamic environments [10]. This capability allows real-time decision-making, thus enabling AMRs to dynamically change travel routes whenever environmental changes occur [26]. However, despite their relative flexibility, AMRs face problems arising from congestion management and task management, especially under conditions of high density traffic, because heavy traffic may result in congestion and increased travel time [10].
- **ACMR:** At the forefront of technology, ACMRs combine the adaptive behavior of AMRs with dedicated techniques to handle multiple cases for precise operations at a case level. Unlike AGVs and traditional AMRs—which are typically limited to bulk transport—ACMRs can retrieve individual cases or multiple racks in a single trip, reducing cycle times and improving throughput. Early deployments, such as Hai Robotics' HaiPick system, demonstrate promise [27]Although research on ACMRs is still developing, their adoption in warehouse automation is rapidly expanding.

2.1.4 Research Gaps & Need for Further Study

Significant progress has been made for in AGV and AMR kind of shuttles, but there is still a lack of comprehensive studies on ACMR kind of shuttles. Navigational ability and integration into structured environments well describe AGVs and AMRs however few studies have rigorously assessed long-term performance, cost-effectiveness, and scalability of ACMRs. According to industry reports, in a warehouse that used ACMR kind of shuttles enhanced order processing efficiency by 30% during peak periods [28]. However, not much has been said with respect to the initial cost of the technology, interfacing problems with legacy Warehouse Management Systems, and cybersecurity issues [29], [30].

As Hai Robotics pointed out, ACMR kind of shuttles offered significant improvements in operational productivity by means of higher storage density and picking rates [28]. Future research must focus on developing standardized measures of performance and benchmarking studies to effectively assess the Rate of Investment for warehouse shuttles specifically for ACMRs across different operating settings. This review therefore paves the way for further studies on warehouse automation systems that includes usage of three different kind of shuttles AGVs, AMRs, and ACMRs, with an emphasis on overcoming the limitations of existing technologies.

2.2 Overview of Warehouse Automation

2.2.1 The Drive Towards Automation in the Era of E-commerce

The exponential growth of e-commerce has transformed logistics and warehouse operations revolutionarily. As the consumer demands increase, accurate delivery increasingly, companies are forced to rethink labor-intensive manual processes. Order picking is often employed as the most labor-intensive process in warehouse management, accounting for 50–55% of all operating expenses for manually operated warehouses[31], [32], [33]. Its high-cost ratio consists primarily of the great amount of time that the pickers actually spend walking between storage positions, which amounts to some 55% of total working time. The figures represent significant inefficiencies plus major costs locked in traditional ways of manually fulfilling orders.

Even a minor error in picking an order causes long delays and costs to escalate, leading to the requirement for highly reliable automated solutions. Growing competition and complex orders are pushing warehouses toward full automation and optimized systems, driven by the need for speed and efficiency [14]. That's why, companies now increasingly invest in automation technology, which encompasses the entire operation from sorting and inventory management to perfectly accurate order picking. This not only saves labor cost but also lowers errors while enhancing overall throughput. Automation reported approximately 20% savings in the cost of operations per warehouse in addition to miserable annual savings [1]. Automation reduces cycle times, speeds processing, enhances accuracy, thus providing a competitive edge to businesses in the fast-changing market [24].

2.2.2 The Rise of Warehouse Automation

The traditional warehouse order picking process has been always labor intensive and error prone. Earlier when the volumes of the order were small, and the warehouse had not yet transitioned into high-volume, high-activity periods such as Black Friday or Cyber Monday, manual operations sufficed. [32]in their preliminary study found that more than 80% of warehouses in Western Europe still follow the human-centric picker-to-parts system, where human pickers moved over the shelves to retrieve items instead of robot shuttles. Such inefficiencies were responsible for a considerable amount of unproductive walking time that negatively affected productivity.

The first automation aspect involved the use of AGVs, in which manual transport activities were replaced by the shuttles that follow fixed-predefined paths. AGVs, introduced in mid 1950s, were mostly used in structured industrial environments like manufacturing and distribution centers [34]. Their ability with pre-defined paths, magnetic, or laser-guided navigation to move pallets consequently accounted for remarkable decrease of labor cost. Studies indicate that AGVs help to reduce labor expenses through automation and reduced human intervention [2], [35].

As technology became advanced, Emergence of using AMR shuttles increased. AMRs introduced dynamic navigation capabilities through technologies such as Light Detection and Ranging (LiDAR) and Simultaneous Localization and Mapping (SLAM), unlike AGVs. This means that AMRs become adaptable to the changing warehouse layout. [36]. Ocado, for example, introduced AMRs in its semi-automated grocery fulfillment centers to improve speeds in order processing and lessen travel time.

Today, the latest generation of ACMRs shuttle builds on these features, combining highly developed case-handling capabilities with very precise navigation. Achievements have already been shown by industry leaders such as Hai Robotics, demonstrating that an ACMR shuttle can move through multiple racks in one trip up to 30% lower in order cycle time while improving efficiency and storage density in operation [28]. Despite such promising advances, academic research on ACMRs is scarce; hence, an important area for further investigations.

2.2.3 Integration Challenges & Technological Enablers

The main challenge in modern warehouse automation is integrating diverse technologies into one cohesive system. In the traditional systems, AGV kind of shuttles are tied to a fixed infrastructure, and integration with the Warehouse Management Systems (WMS) is quite straightforward; however, with warehouses changing and moving, the need for dynamic systems has now brought AMR and ACMR kind of shuttles, which requires more sophisticated integration to the warehouse.

Modern warehouse integration increasingly employs Internet of Things (IoT) and cloud-based platforms. Real-time information on inventories, environments, and status of equipment, contributes to seamless robot and central system communication [37], [38], [39], [40]. Cloud-integrated logistics systems also increase automation in warehouses by decentralizing as well as coordinating decision-making among various autonomous units communication [31], [41]. The utilization of data-sharing technologies for AGV communication and cooperation further enhances operational efficiency.

The pace of warehouse automation is rapid enough that facility operations have made profitability improvements like throughput, storage density, and accuracy of picking [42]. They present real-time data on which operational decisions can be taken so that inefficiencies can be minimized, as well as improved responsiveness to fluctuations in demand.

Newly emerging technologies such as blockchain are under study toward securing communication protocols and creating an irreversible record of robotic operations. However, there is a significant problem for providing security and privacy for robotic-based smart logistics since devices such as unmanned delivery trucks, shuttles and drones are very much prone to possible cyber threats. Public-key cryptosystems seem to be a promising solution, as they encrypt sensitive messages to give integrity to data and prevent unauthorized access [30].

2.2.4 Timeline & Evolution of Warehouse Automation

The evolution of warehouse automation has very much been a development process fueled by the changing demands of the marketplace:

- **1950s to 1970s:** Some of the first automatic solutions and the prototypes of AGV shuttles were being developed with the goal of making the use of human labor for assisting in handling materials very painless. The first examples of AGVs started to operate, with the effective and efficient movement of materials since 1955 [34]. These early AGVs were dependent on simple guidance systems using magnetic or optical tracks which laid further groundwork for future improvements.
- **1980s:** the AGVs were already in use for the internal transport in warehouses, distribution centers as well as production environments, especially in regard to operations needing repetitive traffic patterns [43].
- **1990s to 2000s:** Developments in sensor and digital control technologies contributed to AGV systems that were more sophisticated in terms of reliability and load carrying capacity.
- **2010s:** This decade saw a fundamental shift take place in warehouse automation through the incoming of AMR shuttles, and wide adoption laboratory processes employed in most parts of successful companies. A revolution took place nearly in 2012, when Amazon brought Kiva Systems deployed AMRs in its fulfillment centers, revolutionizing warehouse operations.
- **Late 2010s-Presently:** ACMR shuttles are the most recent stage and have integrated fine multi case-moving with sophisticated autonomous navigation. The AMR acceptance exploded in the late 2010s, and by 2025 more than 50,000 warehouses will be operating using over 4 million mobile robots, an unprecedented shift for warehouse logistics, according to industry forecasts [14].

An evolution viewpoint discusses that each technological leap made with time tried to address respective operation issues whose success would pave way to more adaptive and efficient warehouse systems.

The whole journey of shuttles used in the warehouse automation from AGVs to AMRs and ACMRs is in a pretty clear direction - toward more efficient, scalable, and dynamic systems [24].New improvements in the future on e-commerce will introduce advanced technologies of IoT, cloud computing, blockchain, which will further enhance automation [12]. AGVs and AMRs have received the brightest spotlight in previous research; ACMRs are still emerging technologies in desperate need of deep academic investigation. This overview sets the backdrop for in-depth reserved exploration of these technologies and the development of optimized, integrated automation systems designed to meet with the challenges of modern warehouse operations [5].

2.3 Optimization Strategies for Multi-Robot Warehouse Systems

For this chapter the most related 50 research papers are used and analyzed.

2.3.1 Task Allocation in Robotic Fulfillment Systems

Optimizing the task allocation affects the overall throughput with usage of resources, and cost assets in robotic warehouse systems. It becomes even more critical when orders become more complicated and warehouse automation becomes more routine, such that a robot shuttle should be assigned the correct task at the best time. Studies show that an improper allocation could reduce efficiency by up to 20% through unnecessary robot idling and congestion [14]. Figure 2.1 shows the percentage distribution of most used task allocation approaches identified across the reviewed literature.

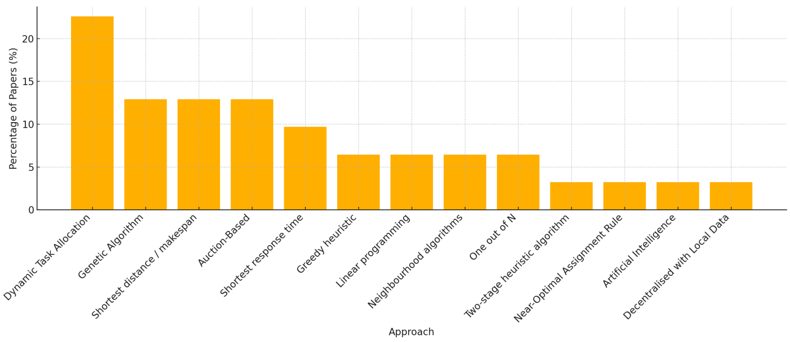


Figure 2.1: Comparison of Usage of Task Allocation Approaches

Based on this analysis, the various approaches categorized into four major categories based on their robustness to task assignment, as well as their relevance in various situations. Hence, we will consider optimization-based approaches, heuristic-based approaches, decentralized coordination approaches, market-based approaches, and AI-based task allocation mechanisms.

Optimization-Based Approaches: Optimization methods are the most widely celebrated methods among these categories, with almost 39% of all the reviewed works relying on such methods. Shortest Distance/Makespan, Shortest Response Time, Linear Programming, one-out-of-N rules, and near-optimal assignment rules are in this group of methods. Most of these strategies seek to pair tasks to robots in the most efficient manner relying on mathematical formulations and deterministic rules. While performances are guaranteed through Linear Programming for optimal allocation, it is not suitable for real-time applications due to its high computational cost, [5], [44]. In contrast, the lightweight Shortest Distance and Shortest Response Time algorithms can perform acceptably in dynamic environments, albeit at the expense of global optimality.

Heuristic-Based Approaches: Heuristic approaches are another class that contributes a fair amount of weight around 29% to the studies under review. The method includes Genetic Algorithms, Greedy Heuristics, Two-Stage Heuristic Algorithms, and Neighborhood Algorithms, which are appreciated for their simplicity and flexibility. This observation is best with respect to Genetic Algorithms, which optimize task assignment iteratively on the basis of evolution, showing task efficiencies improved by up to 15% [25],[45]. Heuristics are not guaranteed to return global solutions, but lower overhead means they typically perform well in practice.

Decentralized Coordination Approaches: A little more than 26% of the studies use decentralized coordination strategies, allowing the robots to make autonomous decisions based on local data or cooperative protocols. Among the approaches under this class are Dynamic Task Allocation and Decentralized Allocation with Local Data. These methods are known to enhance system scalability, flexibility, and robustness in large-scale warehouse operations. Furthermore, they assist in alleviating bottleneck effects due to the autonomous negotiation and execution of tasks [46], [47].

Market-Based Approaches: Market-based mechanisms, particularly Auction, represent 13% of the analyzed studies. This method relies on a bidding system where robots independently bid for available tasks according to local cost functions such as travel distance or battery level. This category is strong for its ability to dynamically balance workload among agents in a decentralized mode [48], [49]. Although efficient and scalable, they need to be well-designed to avoid bidding conflicts and distribute tasks poorly.

AI-Based Approaches: Artificial Intelligence techniques were the least explored, being given 3% of attention in the reviewed literature. These approaches are usually characterized by the real-time adaptation of task assignment decisions using learning-based algorithms. While there remains a promise for continued AI-based auto-allocation from the existing literature, its actual adoption remains very limited. On the other hand, increasing attention has been paid, as suggested by recent trends, to real-time analytics and adaptive AI algorithms for enhancing the effectiveness of allocations in environments that become more and more complex.

2.3.2 Path Planning Algorithms for Shuttle Robots

Path planning is essentially what would ensure optimized navigation of the robot whereby energy consumption would be as less as possible with orders being fulfilled in time. Out of the 50 studies, 38 were investigating algorithmic advances to achieve minimized distances traveled and, at the same time, avoid congestion. It could increase order-processing time by 40% in denser warehouses [7]. Figure 2.2 shows the distribution of individual sub-methods used within each task allocation group.

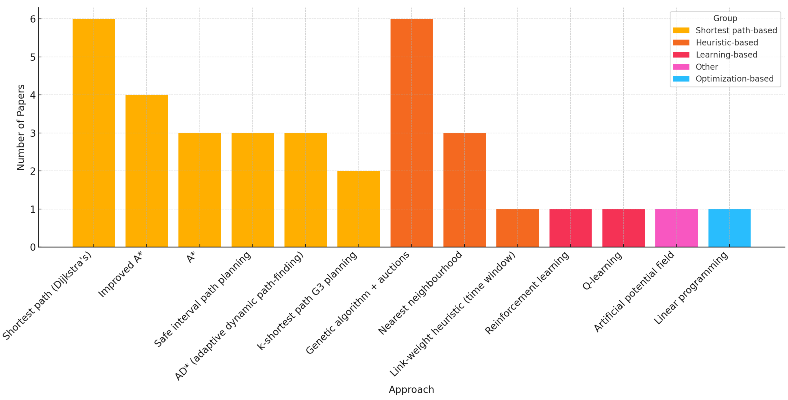


Figure 2.2: Grouped Bar Chart: Sub-methods within Each Group

Shortest Path-Based Techniques: This is the most common group of methods, which is used in 60% of the reactive studies. Among Dijkstra's algorithm, 17.4% of the usage claimed it offered globally optimal paths. Yet, its deployment under large real-time constraints is not appropriate because of its high computational burden [50], [51]. Enhanced variations of A*, Improved A* and Standard A*, were employed collaboratively in 17.4% of the studies as well. Improvements, such as Hierarchical Cooperative A* and Windowed A*, have given a lot of competitive edge concerning scalability and adaptability to dynamic environments [52]. Further, the other shortest-path methods, namely Safe

Interval Path Planning, AD*, and k-shortest path G3 planning, represented 17.4% of the literature, demonstrating the continued presence of the path-planning algorithms in studies.

Heuristic-Based Approaches: Heuristic techniques accounted for 28.9% of the studies, thus providing reasonably good solutions with lower computational times. The most prominent method in this group is a Genetic Algorithm combined with Auction mechanisms, applied to 17.4% of the reviewed studies. Fast algorithms under dynamically changing warehouse conditions were aided by other methods, such as Nearest Neighborhood and Link-weight Increment Heuristics, which corresponded to 8.7% and 2.9% of the studies, respectively.

Learning-Based Approaches: Learning methods such as RL and Q-learning appeared together for 8.7% of the reviewed studies. RL allows robots to dynamically fine-tune their navigation behavior based on learning from past experiences and currently perceived environmental feedback. Though these methods haven't been fully utilized, they show tremendous promise for warehouse automation systems in the near future [53], [54].

Optimization-Based Approaches: Mathematical optimum path assignments are achieved using linear programming, constituting 2.9% of studies. However highly precise , computational overhead makes it extremely unfeasible and largely limits its use to small-scale applications or offline scenarios.

Other Approaches: Artificial Potential Field (APF) techniques were used in 2.9% of the reviewed studies in which obstacles are modeled as repelling forces and goals as attractors. In spite of their computational lightness and intuitiveness, APF methods have a tendency to land in local minima problems, with robots being unable to reach their goals [55], [56].

2.3.3 Deadlock Prevention & Traffic Direction in High-Density Warehouses

When multiple robots block one another's paths, the situation is referred to as a "deadlock." And such deadlocks can be incredibly costly in terms of productivity. Out of the 50 reports about deadlocks, 28 of them discussed methods and techniques to avoid deadlocks. Figure 2.3 depicts the usage of various studies in response to deadlock prevention strategies in the pie chart.

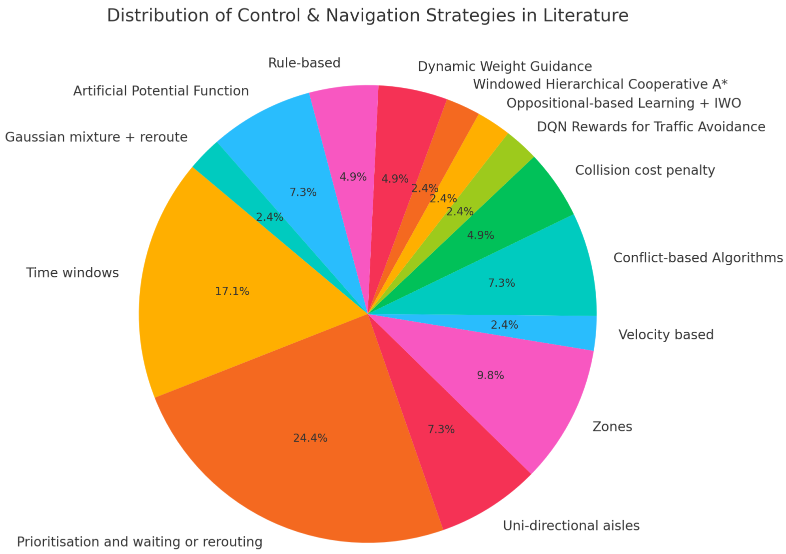


Figure 2.3: Distribution Of Control & Navigation Strategies In Literature

Prioritizing Techniques & Waiting - Rerouting Techniques: This figure was the most widely employed strategy in the literature, manifesting in 24.4% of the reviewed studies. These involve pausing or rerouting the robots to conform with traffic coordination techniques in terms of the emergencies encountered, in order for them to move through areas of congestion or path conflict. They are very effective in deadlock reduction and system flow improvement in high-density warehouse environments [10], [57].

Time Window Strategies: Applied in 17.1% of the studies, the time window techniques involve making time intervals available for access by the robots to shared zones or resources to minimize the interference of one path by another and, thus, also the occurrence of collision. It is most important in working areas where dense operations are happening simultaneously [20], [58].

Zoning & Uni-Directional Aisles: Zoning procedures, used in 9.8% of the studies, are such that joining spatial distinctions along logical areas would lead to reduced inter-robot conflict and better coordination within intersections [34], [44]. Uni-directional aisles (7.3%) naturally eliminate head-on path collisions, thus fostering a more fluid movement of traffic in narrow aisles.

Conflict-Based & Collision Avoidance Strategies: Conflict-based algorithms, or those presented by the study in this proportion, 7.3%, allow the user to detect the conflict beforehand or manage it through rerouting or temporary reallocation of tasks. Also similar to the above is that collision cost penalty methods, or those under 4.9%, assign the numerical cost of potential collision paths between robots which make them avoid moving over crowded areas dynamically [59], [60].

Artificial Potential Function (APF) and Rule Based Methods: APF-based techniques, which were utilized in 7.3% of the studies, demonstrate repelling forces from obstacles in the path of robots as attractive forces toward goals to direct the robot's motion. Such an approach, however, becomes prone to substantiating robots falling into local minima, where the robots get trapped in the suboptimal pathways [20]. However, on the deterministic side rule-based methods which incorporated 4.9% of the studied technique did use pre-determined decision protocols, although less flexible in highly dynamic environments.

Emerging and Hybrid Techniques: The least portion of the literature (2.4%-4.9%) considers advanced or hybrid techniques such as Dynamic Weight Guidance, Windowed Hierarchical Cooperative-A*, constantgage segmentation for rerouting, etc. Hierarchical Cooperative A*, as featured in 6 studies, is known to improve coordination in real-time warehouse operations [1], [49]. These strategies indicate rapid movement from intelligent deadlock resolution to dynamic navigational capability, paving the way for the next generation-plus robotic traffic system environments.

2.4 Automated Guided Vehicle Shuttles (AGV)

2.4.1 Introduction to AGV Shuttles

AGVs have been around for several decades for warehouse automation, performing the monotonous task of transporting materials along fixed routes and thus revolutionizing the traditional methodology in material handling into more efficient, safe, and big-time economy in labor cost. AGVs efficiency and speed of transport have also improved, with some studies reporting a drop of up to 23% in service time.[61]. Other studies also revealed that AGVs helped in lowering labor costs by minimizing overtime payments and operational inefficiencies[35], [62].The chapter thus takes a macro-overview of AGVs' technical evolution, operational benefits, and inherent limitations. It serves as the foundation for understanding how AGVs still revolutionize automated warehousing and logistics.

2.4.2 Technological Bases of AGV Shuttles & Capabilities

AGV success rests upon a very high level of integration of hardware and software components which give strong navigation and operation. The following are the technology components of AGV systems:

•**Navigating & Guiding Systems:** Modern AGVs use quite a number of sensor technologies in order to pursue the predefined route with high precision. Magnetic guidance is still one of the oldest and most cost-effective methods, and it is now supplemented by even more advanced technologies. Optical sensors and laser scanners provide higher resolution monitoring and dynamic relocation capabilities for improved navigation accuracy. RFID has also been investigated as a way for AGVs to detect and confirm their positions with respect to fixed reference points in warehouse environments; however, it is virtually nonexistent in applicability to AGV navigation in comparison with vision-based and lidar systems. While sensor fusion technology has contributed significantly to improved AGV performance in recent years through the integration of multiple sources, it is expected that its effectiveness will increase with improved localization and obstacle detection. Today, it is an in-use technology behind modern autonomous intralogistics systems processing by AI and with a wide range of triangulated sensors, adapting to highly dynamic, warehouse environments [63].

•**Control & Communication Centrally Managed:** Many AGV systems are so configured that a controlling centralized master takes care of vehicle location tracking, routing, and job assignment. With each vehicle, the central unit communicates in real time about the optimal motion planning and coordination of paths [45]. For AGVs to ensure effective communication, strong protocols are being used, which are a combination of wired networks and wireless data links for example, MQTT-based communication mechanism, thus allowing real time updates between AGVs and the master controller [64], [65]. While centralized control systems for AGVs have proven to be optimal for coordination under static conditions, they do not have a very satisfactory scalability. Current centralized solutions almost never support fleets larger than 10–15 AGVs without considerable slowing in communication and computational bottlenecks [66], [67] .

•**Power Systems & Battery Management:** Real-time information on battery power life has carried sophisticated battery management systems onboard AGVs for automated recharging and optimum energy consumption in high-demand uses, especially in high-pick warehousing [68]. Inductive charging has been categorized as a very good alternative to the old plug-in charging, having the potential to minimize downtime and increase fleet availability . Other strategies such as predictive maintenance with preventive and corrective approaches have also been shown to maximize AGV uptime, along with increasing battery life [19]. While smart power management algorithms are being proposed to optimize modes of charge cycles based on variations in workload, energy efficiency still depends on the specific warehouse configurations and operational demands [57].

•**Structural Design & Load Handling:** AGVs are constructed to hold heavy load bearing components-they are maneuvered to move single loads, often one pallet or one shelf per trip. The transportation is in a formal way: A load request is generated from the origin then. While some research has shown that multi-load AGVs might enhance fleet efficiency, one-load-carrying AGVs still constitute the majority of design-wise features due to reliability and simple scheduling [69]. While the design feature is oriented to accuracy and reliability, it also may potentially reduce the throughput rate in an environment where concurrent transportations may be more effective [34].

•**Integration of The Warehouse Management Systems (WMS):** Interfacing with AGVs significantly increases the efficiency of real-time inventory synchronizations as well as routing of the vehicles. By prioritizing order management processing, dynamic tracking of inventories, and automatic scheduling of tasks, WMS ensures that the storage flows and resources are optimally utilized in the warehouse operation. WMS lead to minimized delays in task accomplishment through automated scheduling algorithms like shortest-job-first (SJF) and tab search [70].

2.4.3 Advantages of AGV Shuttles

In controlled static environments, AGVs provide a number of operational benefits:

•**Consistency & Reliability:** AGV working advantages are like those in typical warehouses today under controlled conditions. The repetitiveness of action by AGVs is ensured by their movement on predefined paths, because of high determinism. Being ever tireless and accurate to the last detail in planning a route, such throughput is guaranteed even with around-the-clock operations for a facility that to never gets interrupted. Success under such conditions is known as consistency in the mass production line where inconsistency may lead to a disaster of huge scales: time lost for production. In terms of production figures, AGV-based factories have shown great improvements by drastically minimizing error rates through optimized scheduling and advanced path planning algorithms [4].

•**Improved Safety in the Workplace:** AGVs have drastically attributed to accidents happening in workplaces. Due to the automatic processing of heavy loads, it reduces the rate of manual handling thus preventing accidents to workers and lowering the rate of musculoskeletal injuries. AGV systems incorporate integrated safety features like collision detection, emergency stop capability, and duplicate sets of sensors which further boost workplace safety. Research showed that AGV implementations contributed to decreasing workplace hazards owing to the limitation of human involvement in more high-risk jobs leading to general improvements in occupational safety standards[71], [72].

•**Handling Accuracy of Material:** Route pre-programmed strictly has guaranteed AGVs to handle goods with high positional accuracy. This position is important mostly for plants such as car assembly, where reputation for assemblies can suffer due to minor errors. The predetermined nature of how an AGV works assures reduced cycle times effective manufacturing and bottlenecks elimination. Research has shown that the AGV picking systems majorly benefit the warehouse workings through improved order accuracy and optimized material transport paths for better high precision in handling and storing operations [73]. Within a more advanced WMS, AGVs also improve the management of inventories and order accuracy of fulfillment.[74].

•**Economic Benefits of Stable Environments:** AGVs are major areas of cost reduction in warehouses having measured production cycles with almost controlled facility designs. They save money through process efficiency and removal of the manual labor requirement and continue to demonstrate less operational cost for automation in many industries. Research shows that AGVs help increase the throughput of the system, reduce labor cost, and lower stock inventory, which leads to considerable cost savings [2]. One mega distribution center alone, operating with over 500 AGVs, experienced throughput that increased twofold along with total cost savings realized when utilizing Kiva robots, which are well-known as efficient devices in the fulfillment operations of Amazon [24].

•**Scalability for Fixed Environments:** AGV systems are definitely scalable in factories where they have organized and fixed layouts. The fleet operates in synchrony under the controls of a central managing system so that each additional vehicle can be brought in without introducing operational uncertainty. Research has shown that AGV picking systems are highly scalable because they allow easy adjustments in the number of fleet, inventory shelves and picking stations as demands for operation changes [24], [4], [75]. Scalability has been a key factor in wide adoption of AGVs in large manufacturing and distribution centers where efficiency and flexibility are highly demanded.

2.4.4 Limitations & Drawbacks of AGV Shuttles

With many advantages, AGVs are still troubled by a number of inherent limitations that restrict their performance, especially within more dynamic and changeable operating environments:

•**Fixed Path Design:** Fixed paths are good for guiding the equipment precisely; however, these paths cannot be altered when the warehouse gets reconfigured. Any changes in layout, such as moving a storage block or putting in a new line, require not only reprogramming but also large-scale installation of guidance devices. The inability to change creates a twofold penalty: it costs money and brings the system down, thereby reducing effectiveness. AGV shuttles serve to create automation; however, such pathways fixed can become limitations in warehouses that undergo dynamic modifications, considering that extensive efforts will be required to reconfigure these pathways when the layout changes [76] .

•**Operating Limitations: Single Task & Re-handling:** The AGVs are inherently designed to carry one full pallet or shelf per trip. In normal operation, an AGV brings a shelf to a drop-off point where a human operator picks the needed items. Once the picking is complete, the AGV needs to return to the original storage location to retrieve the next shelf. This round trip, which incurs several stops and re-handling of the same shelf, will increase the cycle time and operating cost. AGV systems, by nature, tend to suffer with regard to task re-handling inefficiencies, especially in dynamic environments where they experience difficulty adapting to pick-and-place operations [3].

•**Centralized Control Bottlenecks:** While a centralized control system minimizes coordination complexities in fixed setups, it represents a bottleneck as the complexities of the system increase. The central unit collects massive real-time information from all AGVs in large-scale operations, yielding communication latencies and inefficient route decisions. This leads to bottlenecks retarding responses occurring in peak times, which in turn impair general effectiveness. The studies show that due to a centralized control scheme, scalability is a big issue: as the system scales, the computational complexity of realizing control objectives becomes increasingly difficult to cope with [45]. To further add to the delays, AGVs are slower to react to emergency situations like accidents or sudden obstructions, as they do not have the independence to make on-the-spot decisions.

•**Maintenance & Reconfiguration Challenges:** The success of AGV shuttles are dependent frequent maintenance and accurate calibrating. Under environments with periodic physical layout changes-some modifications to floor stripes, some obstructions, or new construction-the upkeep of the whole AGV network requires recalibration. Such maintenance increases the maintenance overhead and leads to unexpected downtime, thus further increasing operational costs. Multi-AGV systems must be in constant adjustment of their maintenance planning using advanced scheduling algorithms in order to prevent failures and sustain reliability of the whole system [6]. A poorly thought-out proactive maintenance approach can cause operational disruptions, which can build up and lead to adverse levels of inefficiencies in automated warehouse systems.

• **Economic Trade-offs Due to Dynamic Environment :** Usage of AGV shuttles are very well researched and seen to be cheaper when used in a static environment, their usage becomes questionable when dynamic operational and layout needs arise. The economic cost related to paying high maintenance and service costs connected with constant reconfiguration, recalibration, and, in cases of other short-term AGVs required to offset the single-task limitation, can actually nullify the promise of return on investment. Research has shown that while AGVs are best-used solutions in structured warehouses, their powers are limited in this respect when we have a dynamic environment due to the high costs of system refurbishment and layout changes incurred whenever interfering with AGV operations [51]. Thus, while AGVs prove economically justifiable in stable environments, they often give way to inefficiency and unadaptability in warehouses undergoing frequent reconfigurations.

2.5 Autonomous Mobile Robot Shuttles (AMR)

2.5.1 Introduction to AMR Shuttles

AMR shuttles stand to gain warehouse automation for the future. In contrast to their older version AGVs that insist on following fixed predefined paths, AMRs locate their paths through dynamically changing environments with the aid of sensor technologies, artificial intelligence (AI), and real-time data processing. Thus, AMRs manage alterations to classic layouts with up to a 20% increase in order-processing throughput, evaluated under the independent study of autonomous forklift systems by DHL [77]. This chapter discusses a comprehensive literature review on AMRs, technological base, operational advantages, drawbacks.

2.5.2 Technological Bases of AMR Shuttles & Capabilities

AMRs rely on a developed technological platform differing in many ways from that of AGVs. These unique capabilities include:

•**Sensor Technologies, SLAM & AI-Driven Control Systems:** AMRs are dependent on the aggregation of technologies for getting navigation through dynamic warehouse environments. LiDAR, 3D cameras, ultrasonic sensors, and RFID systems can be counted as the most crucial among these technologies, which allow robots to view themselves as three-dimensional entities. To perceive the environment around such robots, they have Simultaneous Localization and Mapping algorithms to construct and update real-time digital maps, allowing them to autonomously plan paths and dynamically reroute based on changes in conditions [10]. Coupled with this sensory framework are machine learning and artificial intelligence (AI) systems, which will be the cognitive core of AMRs. Such AI-based control architecture is able to enable real-time processing of inputs from sensors into detecting obstacles, optimizing the routes, and predicting hazards [10].

•**Decentralized Control Architecture :** Decentralized task allocation allows AMRs to dynamically allocate task assignments reducing scheduling downtime and improving the operational efficiency of an AMR system. Studies demonstrate that decentralized scheduling and task allocation mechanisms such as auction-based or hormone-regulation strategies give flexibility and responsiveness to AMR operations. For instance, [78] proposed a decentralized allocation of task cooperative and distributed scheduling, facilitating dynamic communication among vehicles and machines, thus leading to improved scalability for large-scale deployments.

•**Power & Energy Management:** AMRs employ advanced battery management systems that track energy consumption and optimize energy usage while facilitating fast recharging through wireless and quick-dock technologies. Such recent advancements have greatly minimized battery charge downtime and improved the overall efficiency of operations. Research shows that wireless power transfer solutions eliminate wired charging connection, thus ensuring 24/7 uninterrupted operations in a warehouse where continuous performance is of utmost priority [79], [10].

•**Integration of the Warehouse Management Systems (WMS):** Integration of real-time data allows for dynamic scheduling, route optimization, and responsive order fulfillment. When this integration is implemented, studies have shown that throughput can increase by 20 %, as operational decisions are based on real-time inventory and order data. Prime examples include Amazon, the most successful e-commerce company, which automated their order fulfillment by acquiring Kiva Systems in 2012 and that secured notable gains in operation, reducing warehouse operating costs by 20 percent and picking costs per fulfillment center by $22 million [1].The real merit of AMRs for warehouse automation is in delivering items directly into the hands of pickers in a goods-to-person (G2P) system. Such a system eliminates unnecessary worker movement and optimizes warehouse operations, and is already being touted as one major model successful in use by leaders in the industry [24].

2.5.3 Advantages of AMR Shuttles

AMRs have very strong advantages over traditional AGVs for dynamic warehouse applications:

•**Dynamic Navigation & Real-Time Flexibility:** AMRs use real-time environmental sensing, including 3D LiDAR, to continuously update their virtual maps and adapt their navigation paths dynamically to go around both static and moving obstacles [80]. By using topological maps in synergy with deep reinforcement learning algorithms, AMR shuttles optimize a global path planning and adjust their optimize dynamically routes to guarantee efficient navigation in changing warehouse environments. Such adaptive navigation strategies, as demonstrated in large-scale deployments by Amazon's multi-robot coordination system, have been shown to significantly enhance operational efficiency by minimizing travel time in dynamically configured warehouses.

•**Increased Order Processing & Throughput:** AMRs eliminate the backhauls inherent in an AGV routine robots picking up freight at a shelf, waiting for a human picker, and then returning to pick up the next load-so there is material handling efficiency and more direct order fulfillment moving freight from pick points to pack stations, with less downtime and throughput efficiency [14]. Studies have shown that the utilization of AMRs increases order handling efficiency by about 20 percent, thus reducing costs for warehouses and increasing operation speeds [81].

•**Increased Task Flexibility:** AMR shuttles are multi-task automation units; it can pick, sort, move goods in one command system. Programmed programs possess various functions, which reduce manual labor in addition to enhanced productivity in operations. According to [48], these AMRs bring in 20% savings on labor costs in CLS automated fulfillment systems, exhibiting optimized task-allocation efficiencies and less human input.

•**Scalability & Flexibility:** Distributed architecture of AMRs makes it highly scalable, where new robots can be easily pulled into existing operations without major reconfiguration. AMRs, equipped with onboard intelligence and decentralized decision-making, differ from AGVs. This allows the robots to autonomously adapt to dynamic environments [10]. AMRs does not require a fixed infrastructure, such as magnetic strips; therefore, this flexibility leads to a decreased cost of installation and maintenance. They offer a prospective high-throughput, scalable, and adaptable solution for modern warehouses. Companies that change from AGVs to AMRs will find that their computational efficiency increases, reliance on centralized control decreases, adaptability in dynamic environments is better, and all these parameters substantiate cost reductions [82].

2.5.4 Limitations & Drawbacks of AMR Shuttles

Although it boasts many advantages, however, there are some few disadvantages of an AMR, which are:

•**Traffic Congestion & Coordination Problem:** Independent movement of several AMRs especially in crowded areas such as corridors and intersections within warehouses leads to congestion. Order processing can get delayed due to congestion within warehouses during peak hours. Studies indicated that high-density AMR deployments had increased travel time related to unavoidable congestion and dynamic rerouting issues. This, in turn, prevents them from being as efficient for example, in decentralized decision-making among AMRs, which may at times lead to inefficient task allocation, whereby more than one robot is assigned to the same task, with longer travel distances, thereby making it not totally efficient. The last measures are hybrid traffic management approaches that combine decentralized path planning with centralized conflict prediction to improve coordination and reduce delays [83] .

•**Communication Interference:** AMRs exchange information among themselves and with central systems via wireless communication. High radio frequency interference and consequently signal loss degrades performance, especially towards the simultaneous localization and mapping (SLAM) accuracy. According to studies, communication disturbances lower SLAM accuracy up to 10% affecting real-time navigation and coordination efficiency. Attempts to solve such problems are the development of adaptive communication protocols and double schemes for localization [84]. AMRs can function within the noisy conditions of the warehouse taking into consideration harsh environments.

•**Calibration &Maintenance Constraint:** AMRs would require some amount of calibration and maintenance of proprietary sensors running AI to ensure peak performance. Predictive maintenance methods, including preventive and corrective maintenance, have been shown to enhance reliability in preventing unplanned downtime. Unlike traditional maintenance, which comprises both corrective and preventive approaches, predictive models yield less unscheduled downtime, maximized fleet availability, and fewer full-scale disruptions [44]. Its frequent recalibration, especially in the sensor types that matter for the successful performance and traveling criteria, is for within indoor environments typically changing: warehouse environments. Faults so are often attributed to a mobile robot when reaching the work stations and storages. Thus, constant observation and calibration adjustments will be required.

•**Single-Task Operational Restriction:** Most AMRs are engineered for a single transport task in a single cycle. While they can dynamically optimize routes in the given constraints, that practice limits throughput in scenarios that could otherwise benefit from multitasking for improved efficiency. Usually, AMRs handles loads in single units making them efficient in structured warehouse settings but can be less effective in high throughput environments that demand simultaneous task executions.

•**Energy Management Limitations:** Despite the advancements in battery management technologies, AMRs are still energy constrained, particularly under extremely high use conditions. Frequent battery recharge needs can create bottle necks in charging stations and affect overall system efficiency. Energy related delays can also reduce system availability with possible losses through recharging demand. In essence, these challenges can be countered with refined scheduling of charging assignments, efficient forecasting of battery life in the future, and infrastructure enhancement such as inductive charging solutions [19].

2.6 Autonomous Case-Handling Mobile Robot Shuttles (ACMR)

2.6.1 Introduction to ACMR Shuttles

New developments in warehouse automation, ACMR shuttles will combine dynamic navigation as in an AMR shuttles with specialized mechanisms for multi handling cases. Unlike the AGV shuttles that follow a static route or AMRs meant for bulk transportation, an ACMR can carry many cases or racks in one trip. This helps to ensure reduced number of trips, reduced handling steps, short cycle times and reduced operational costs. Although ACMRs promise improved throughput in warehouses, challenges will include high initial investment costs and complexity of integration. They are particularly impactful in e-commerce and retail logistics, where high-volume, case-level precision is critical.

2.6.2 Emergence of ACMR Shuttles

Emergence of ACMRs was due to demerits of AGV's fixed routes and AMR's bulk transport. Pioneers such as, Hai Robotics, Geek+, and Magazino piloted systems in commercial warehouses by 2019. In recent years, market leaders have begun to deploy the pilot proofs and commercial warehouses with ACMR-type systems. For example, Hai Robotics' ACMRs demonstrated their ability to transport up to nine racks at once and reduce redundant trips by 40% during pilot testing [85]. The initial estimates by industry indicate that such systems would introspect approximately 30% of time associated with order processing and would also reduce labor costs by around 30%. However, ACMRs, being the frontier technology, have not really found a valuable mention in academic literature regarding their long-term effectiveness, scalability, and economics, allowing ample scope for further research on this.

2.6.3 Technological Bases of ACMR Shuttles & Capabilities

(ACMRs) are built based on a high-tech futuristic foundation; they use the best of their AMR navigation technology, augmented by specialized case-processing equipment. Transporting and handling cases in warehouses is made possible through advanced sensing and mapping technologies.

•**Advanced Sensor Suite & SLAM:** ACMR shuttles have an advanced sensor suite composed of high-resolution LiDAR, 3D cameras, ultrasonic sensors, and RFID systems like AMR shuttles. These sensors help create and update the digital map in real-time using Simultaneous Localization and Mapping (SLAM), allowing ACMRs to traverse through very complex and unstructured warehouse environments [80]. 3D LiDAR integration gives precision around surroundings, thereby providing reliable obstacle avoidance and path planning in high-density storage settings. RFID systems augment the navigation robustness of ACMRs in warehouse environments using real-time tracking where precise location points enhance LiDAR-based mapping. This is extremely crucial since high accuracy is required for maneuvering single cases or stacked units available in a tight storage area for operational effectiveness and smooth material flow [30].

•**Specialized Case-Handling Mechanisms:** Unlike AGVs and AMRs, ACMRs are equipped with adaptive gripping and manipulation structures dedicated to sensitive and precise case-level handling. These gripping techniques coupled with real-time computer vision and force sensing allow ACMRs to dynamically adapt their grip based on size, shape, and fragility of the item they are working on. The aisle or multiple rack retrieval of items will allow the order fulfillment process to be optimized. AI path optimization systems would dynamically consider real-time sensor data to deploy routes and manage capacity to move goods rapidly and efficiently.

•**Decentralized Control & Inter-Robot Communication:** ACMRs typically are under decentralized control architectures whereby every robot makes its own decision based on local data. This decentralized approach improves responsiveness, especially in high-density environments, where task-allocation delays must be minimized and there is little reliance on a central controller. [12] have found that even in dynamic and unpredictable environments, multi-robot systems with decentralized coordination strategies can perform efficiently. Furthermore, many non-centrally held protocols for inter-robot communication make it possible for ACMRs to share real-time data about what they are seeing and working on, enabling them to collaborate with one another across racks without the need for centralized management. It allows to coordinate actions of robots automatically, reduces conflicts between robots, and thus increases workflow efficiency [83].

•Integration of the Warehouse Management Systems (WMS): The Warehouse Management Systems (WMS)-Enterprise Resource Planning (ERP)-software interaction is very much crucial to the optimal performance of ACMR. Dynamic routing integration and real-time data transmission enhance throughput rates, with studies suggesting that there may be even higher throughput when it is fully interfaced with the digital stock systems [86]. Certification of common communication standards facilitating streamlined interoperability could reduce implementation time and complexity [24]. As these technologies advance, a synchronized operation for ACMRs and warehouse infrastructure holds great potential as a focus area for further R&D.

2.6.4 Advantages of ACMR Shuttles

The ACMR, compared to an AGV and AMR system, holds so many obvious strengths that one can be said to be in service of multi-rack and fine-grained tasks:

•Increased Throughput & Multi-Rack Handling: ACMRs, unlike AGVs that transport one shelf on each trip, are responsible for moving racks or cases in bulk to avoid unnecessary travel time and improve warehouse efficiency. Certain ACMR models, such as the A42 from Hai Robotics, allow for simultaneous carriage of up to 9 payloads on multiple storage trays. This is a huge throughput improvement while saving aisle space up to 50% [28].

•Cycle Time Reduction & System Efficiency: The literature has well established the advantages of zoning and dynamic task allocation in terms of cycle time decreases in robotic fulfillment and AVS/RS systems through queuing network model simulations [4],[87]. While there are currently no studies directly analyzing ACMR in these frameworks, the flexible routing and decentralized decision-making capabilities distinguish ACMRs such that they likely can deliver enhancements on the traditional AGV efficiency gains.

•High Flexibility & Adaptability: The ACMR shuttles are substantially flexible, therefore making it ideal for a highly dynamic warehousing environment. Unlike conventional AGVs that operate along a fixed path, ACMRs have been endowed with the intelligence of advanced sensors and real-time SLAM to self-navigate. This enables them to easily navigate blockages, accommodate changing patterns of the stores' configuration, and accommodate changing priorities of orders [48]. In turn, with dynamic work assignment and smart work sequence, ACMRs do not clog up and improve overall performance.

•**Improved Order Accuracy & Less Handling:** ACMRs ease handoffs and improve order accuracy with automation powered by AI and precision at the case level. Unlike manual picking systems, they deliver consistent performance since the goods are handled by robot shuttles with high precision, thereby minimizing damage and fulfillment error. As an example, in a case study, [85] maximized storage density when 8 robots capable of putting away 2500 racks and picking 700 racks per hour. The development of vision systems, machine learning, and grasping technology is advancing, thereby making ACMR increasingly efficient and reliable.

•**Economic Efficiency in a Heavy Workflow Environment:** Though the capital cost is high, ACMR shuttles are worth the investment as their higher efficiencies which eliminate labor costs, reduce downtime, and improve throughput, outweigh the initial investment. For example, the Magazino TORU robot—capable of carrying up to 16 items—reduces picking costs by up to 50% compared to manual operations. This operational flexibility allows warehouses to rapidly adapt to demand fluctuations without excessive reconfiguration costs, yielding overall savings of 15–20% in automation expenses [88].

•**Scalability Through Modular Design & Cloud-Based Control:** Modern ACMR systems are operationally designed to be modular into existing warehouses. Unlike conventional automation, it does need not vast infrastructures to be changed. ACMRs have adopted most of the open communication protocols and the cloud-based protocols needed [48]. The modular configuration allows the overall scalability of an Advanced Mobile Robotic Fulfilment Systems (AMRF), which has been widely adopted to enhance warehouse performance and flexibility. These systems can level up or downgrade their capacity in response to varying real-time demands, thereby lessening costs associated with reconfiguration while also future-proofing the fulfillment operations for productivity gains and better cost efficiencies [30].

2.6.5 Challenges & Limitation of ACMR Shuttles

While ACMRs are revolutionary, there are some issues that hinder their smooth acceptance:

•**High Start-up Costs & Budget Limitations:** With integration of advanced sensors, AI-enabled software and sophisticated gripper systems, ACMR has a very high capital cost compared with regular AGVs or lower-end AMRs because of the need for high-level onboard intelligence and elaborate functionality that give rise to higher upfront costs [14]. For small and medium-sized enterprises (SMEs), such an investment can be a huge financial handicap, making it impossible to adopt large-scale automation without affordable payment models such as Robotics-as-a-Service (RaaS). ACMRs provide savings over time in terms of both labor and operational efficiency, but upfront capital expenditures remain a significant barrier to widespread adoption.

•**Issue of Interoperability with Existing Systems:** ACMRs require integration with existing Warehouse Management Systems and inventory management databases. They are more of a solution for plug-and-play, whereas custom software, reworking workflows, and providing thorough cybersecurity will come at a huge cost. In responding to this, the vendors are going for cloud-enabled controls and standardized communication interfaces to facilitate easier integration and propagate overall effectiveness [30].

•**Lack of Academic Research & Standard Benchmarks:** Since ACMR technology is still quite new, there are presently no standardized performance measures or thoroughly peer-reviewed publications that evaluate the effectiveness of these systems. Much of the information available comes from internal reports, vendor case studies, and industry analyses; while useful, some of this information lacks the rigor and objectivity normally associated with academic research. Due to the lack of standardized benchmarks, it is difficult to compare ACMRs between different operational factors; this also makes high-certainty return on investment (ROI) assessments and comprehensive cost-benefit analyses difficult or impossible. Absence of industry-standard KPIs means that companies will still need to deal with vendor-specific metrics, complicating cross-system comparisons. As research in warehouse automation continues, it will be important to establish independent, peer-reviewed studies and performance benchmarks that confirm the efficacy of ACMRs across a range of fulfillment environments.

•**Maintenance, Software Updates, & Cybersecurity Threats:** The high-performance and long-term reliability of ACMRs command maintenance and regular software updates for AI and sophisticated sensor technologies. Unlike the conventional warehouse automation system, ACMRs depend on networking controls and effective real-time flow of information, raising several concerns in cyber security. As much as the systems are interlinked, so susceptible to the threats of cyber-attacks like hijacks from remote, data breaches, and spurious systems. The maintenance of good cybersecurity covering encryption, access control, and frequent security patches is absolutely necessary but complicates and raises cost on ACMR operation considerably. Some vendors are improving upon these alarms through a transition toward decentralized architecture and cloud security, which allows for immediate updates and alerting. But the cybersecurity threats are evolving, and ongoing augmentations of the security apparatus are highly required.

2.6.6 Future Direction

Hybrid control architectures aiming to combine decentralized autonomy with periodic centralized supervision hold an attractive promise in improving the major aspects of coordination and robustness-normal control in these issues is the key challenge [10], [89]. The next-generation ACMRs will leverage ultra-high-resolution sensors, state-of-the-art SLAM, and adaptive AI algorithms working together to achieve the lowest cycle times with high reliability.

To streamline integration, cloud control platforms and blockchain-enabled task management would guarantee real-time performance surveillance and secure data sharing studies prove that integration with blockchain may reduce insider threats by approximately 30% [90]. These two models for predictive maintenance and energy-efficient pathfinding cut down energy intake by nearly 12% and also help in minimizing downtimes by almost 15% [91].

It is anticipated that the combination of ACMRs with other systems such as AMRs and AGVs will result in the accumulation of warehouse throughput by as high as 30% [85]. To summarize, ACMRs would be spending considerably on upfront investment and integration hassles at all stages, however, have catchy elements in handling the case and multi-rack technology; their improvement being constant would make them a worthwhile proposition in automating warehouses in the swirl of very fast-growth global electronic commerce.

2.7 Comparison of AGV, AMR & ACMR Shuttles

2.7.1 Introduction to Comparison

The recent advancement in warehouse automation has seen robotic solutions from simple to complex robotic solutions. AGVs have long been the workhorses in structured environments; AMRs extend these capabilities into dynamic, real-time operations, with studies showing that AMRs can increase order processing speed by up to 30% while optimizing space utilization. The emerging ACMRs introduce the latest frontier into autonomy; precision case-level handling with high-end autonomous navigation is enhanced. Such solutions as Magazino's Toru are designed to retrieve and transport 16 items at a time, which should consequently lessen the degree of indecisiveness coming with human labor in e-commerce fulfillment centers.

This chapter presents a compressive comparison of existing systems that considers aspects of navigation capabilities, task specialization, scalability, cost factors, and strategic value.

2.7.2 Navigational Capabilities: From Fixed Path to Adaptive Autonomy

AGVs shuttles have to follow a predefined path. Predefined paths can be exist in many ways. As [10] claimed Conventional AGVs can only follow fixed paths and move to predefined points on the guide path . This brings poor flexibility and result in more downtime with the inevitable change of layouts. In contrast, AMRs can move to any accessible and collision-free point within a given area. By use of advanced sensors and onboard computing facilitating real-time route planning and decentralized decision making, AMR shuttles overcome these limits. This gives power them to adapt quickly since they navigate more dynamic environments than AGV shuttles. ACMRs continue from this evolutionary step in improving multitasking environments. They combine the ability to operate freely, like an AMR, with specialized mechanisms that allow them to handle several cases simultaneously and enhance throughput by managing various loads and working on various tasks simultaneously. The following figure illustrates common guidance method for those 3 different kinds of shuttles (a, b, c, d, e, f illustrates different kind of AGV shuttle, g illustrates AMR shuttle and h illustrates ACMR shuttle).

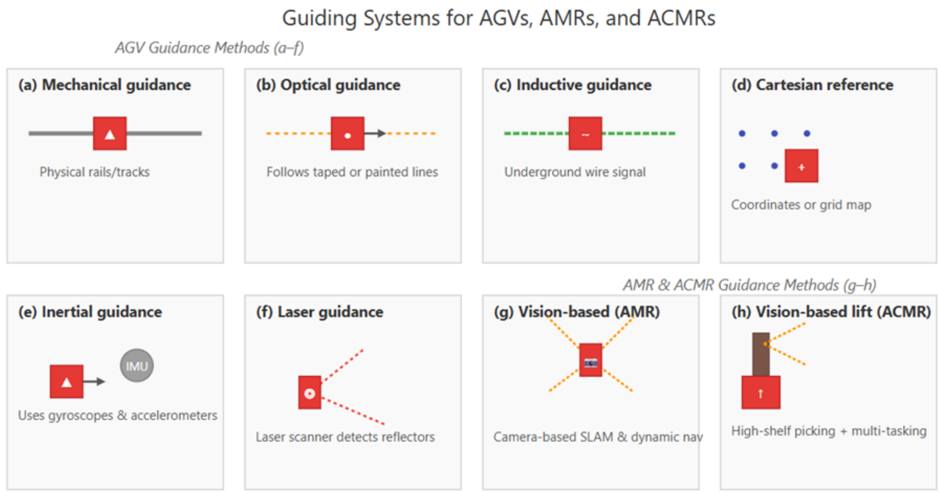


Figure 2.4: Guiding Systems for AGV, AMR and ACMR shuttles

2.7.3 Task Specializtion & Operational Efficeny

Modern automated material handling systems assign tasks to robot types according to their strengths and resultant operational efficiency.

Due to their predictable longitude, repetitive transport operations along predefined routes, an AGV ensures a steady throughput of uninterrupted transport load within controlled environments.

AMRs possess flexible navigation to provide real-time route planning and avoid dynamic obstacles, thus better adapting to changing conditions. This adaptation shortens delays and mitigates operational bottlenecks.

ACMRs offered a further extension of AMR capabilities by dealing with multitasking. No direct citations are found in the literature regarding ACMR. Rather, the design of the ACMR capitalizes on the confirmed advantages of AMR adaptive navigation but adds the advantage of multitasking handling.

These specialized systems work synergistically toward better material handling. For example, [70] the number of vehicles is estimated so as to provide an efficient distribution of tasks and reduce the operational costs of the materials handling system. Moreover, [45] claimed that in decentralized systems by running on each vehicle in the system, the algorithm provides vehicles with capabilities for autonomous path planning and motion coordination. Those findings shows how coordinated deployment of AGVs, AMRs, and by extension ACMRs may further streamline task allocation, reduce cycle time and improve operation effectiveness.

2.7.4 Scalability & Adaptability in High-Density Environment

Material handling systems in high-density operations should be upscaled and adapted on demand with respect to the evolving nature of spatial and load requirements. The traditional AGV systems follow fixed, well-defined routes; thereby guaranteeing a steady level of performance, but sometimes require huge infrastructural upgrades even to increase capacity. Unlike the AGVs, which operate on a preconfigured path, AMRs conduct decentralized management by real-time sensory data, which means it can adjust and change its route to maneuver diverse congested areas. The introduction of multitasking functionality in ACMRs enabled adaptation of the characteristics described by recent improvements.

[46] revealed how deployment of robots can automate the repetitive processes thereby releasing workers for more productive tasks. It can be noted from all these insights that, although AGVs perform well in fixed-path scenarios, the adaptive decentralized navigation possible with AMRs and multitasking capabilities with ACMRs offer much superior scalability and flexibility for applications in high-density warehouse environments.

2.8 Conclusion

In summary, the literature review has provided a comprehensive overview of the current state of research in the field of warehouse automation, focusing particularly on AGVs, AMRs, and ACMRs. The review further elaborates on the evolution and performance attainment of these technologies in fulfilling the heightened necessities of the modern-day logistics setting, especially in task allocation, navigation, energy management, and operational efficiency Research into ACMRs has been almost non-existent, despite the great promise offered by this type of robot with regard to multi-case handling, vertical navigation, and larger scalability, largely because ACMRs have been ignored by both the academic community and comparative studies. With insufficient analytical modeling and empirical studies available on ACMR applications, a strong understanding of the whole dimension is lacking that could be given to ACMR applications in the real world.

For this purpose, this research proposes to fill the identified gap by developing a data-driven mathematical optimization model that integrates ACMRs within a unified framework with AGVs and AMRs. The optimization model will allow a more detailed comparative analysis using performance indicators such as cost efficiency, energy consumption, and speed of task fulfillment. Thus, the outcome will contribute to the theoretical underpinning of robotic work system technologies and decision-making in logistics operations.

3

Mathematical Model

3.1 Introduction

3.1.1 Overview of the Problem

By living in the present world, e-commerce growth, and rapid order-fulfillment requirements have compounded the complexity within warehouse operations. Consequently, robotic systems are being introduced to assist in material handling optimally. Human-operated conventional warehouses contribute to inefficiency, high labor costs, and erratic performance; these render an urgent need for automation of warehouses. To mitigate the different challenges outlined in this context, AGVs, AMRs, and ACMRs are being deployed. Each system has special advantages, AGVs are modeled with Quicktron shelf-to-person robots, follow predetermined paths and have the need for manual intervention during any loading/unloading. AMR models employed are Invia Picker robots, which navigate dynamically and can adjust in real time to avoid obstacles and select optimal delivery routes. Finally, ACMRs use Hai Robotics HAIPICK A42 as a model. It is a high-density storage and multi-case-handling robot that can retrieve 9 cases at once all whilst optimizing vertical motion. However, despite their advantages, these robotic systems face a multitude of challenges involved with Task scheduling-distributing tasks equally among the robots. Energy management-accepting battery life and deciding to recharge. Real-time coordination for collision avoidance and better navigation.

This research intends to formulate a universal mathematical model that unifies the three decision-making processes-AGV/AMR/ACMR-into a single frame. Within this frame, the model will dynamically allocate tasks, optimize energy saving, and maximize throughput at the warehouse. This scalable model is formulated using the scaled values from Quicktron, Invia Picker, and Hai Robotics systems to guarantee realistic performance approximations.

3.1.2 Warehouse Environment

The environment of the warehouse contains storage area, drop-off locations, charging stations, and navigable pathways. The operational mobile robots engage in the pick-and-drop operations while optimizing their speeds to ensure minimal task completion times and energy consumption. The warehouse is built on a grid containing elements such as:

- Shelves S – Storage racks where the tasks are located.
- Pickup locations P – Locations where robots pick up goods.
- Drop-off locations D – Assigned drop-off areas.
- Charging stations CS – Fixed locations where robots go to charge.
- Navigable paths N – Pathways open for AMRs and ACMRs to move through freely.

The tasks are generated on demand using a Poisson process, which simulates the practical scenario of warehouse operations. AMRs and ACMRs, unlike AGVs, can dynamically redirect toward other tasks in real time, nullifying their pre-assigned path in view of delays caused by obstacles, battery constraints, and task priorities. Charging stations are placed strategically to enhance robot operations because battery levels are critical. Thats why charging stations are located between each shelf group. Robots charge at the stations without having to wait for their turn. They autonomously charge the batteries when their levels fall below 20% before carrying on with the task and goes to start point of the robot.

3.1.3 Role of the Shuttle Robots

This research incorporates three different shuttle robotic systems occupied in their respective scopes. The first robot examined was AGVs such as Quicktron Shelf-to-Person. AGVs are robots moving along a predefined fixed-path route and have little or no ability to reroute the path dynamically. They have to be loaded and unloaded manually and stop their operations if a path is blocked. Key characteristics of AGV shuttles can be defined as predefined routes (fixed navigation), stop if a path is blocked (no obstacle avoidance), lastly return to charge when battery goes down under 20%, does one task per trip. The second shuttle robot used was AMR shuttle such as Invia Picker. Fully autonomous, AMRs also perform dynamic path planning with using Dijkstra algorithm. Unlike AGVs, they detect an obstacle and reroute in real-time. Key characteristics of AMR's can be defined as real-time navigation and obstacle avoidance, recharges when battery drops 20% battery before continued operations. And, does one task per trip, and dynamically assigned tasks based on energy levels and availability. The last robot shuttle examined was ACMR shuttle such as Hai Robotics HAIPICK A42. These particular robots are specialized in multi-case retrieval, operating in both horizontal and vertical directions to maximize density storage. ACMRs can perform up to nine tasks per trip unlike AMRs or AGVs. Key characteristics of ACMR can be defined as 3D navigation (optimizes horizontal & vertical movement), handles up to 9 cases per trip, prioritizes multi-case retrieval for efficiency, and Recharges when below 20% battery before continued operations.

3.1.4 Constraints & Challenges

Task Constraints can be defined as AGVs and AMRs can do only one task in a trip, while ACMRs can do up to 9 cases in a trip. Task assignment is evenly distrusted to robots based on the availability and energy states. On the other hand, Energy Constraints can be described as energy consumption in Robots is proportional to distance, they cover and average payload weight. Their batteries will drop below the prescribed levels for operation, recharging at a certain time and allowing robots to charge below 20% charge. Charging stations do not require queue waiting - robots find themselves with an available charger or continue working. And finally, movement constraints were AGV shuttles follow their' predefined, fixed paths, whereas AMRs and ACMRs reroute dynamically. They are able to free move in order to minimize to reduce total travel distance.

3.1.5 Assumptions

Dynamic arrival of tasks has been done based on the Poisson process across the available shelves. Every robot at their predefined start position, starts of every simulation is equipped with a fully charged battery. Charging stations do not require queuing - robots either charge immediately or continue tasks. For shelf to picker AGV shuttle human picker located on drop-off point. Vertical movement for AMRs and ACMRs incurs a time penalty, requiring optimized scheduling. The warehouse layout was designed with 72 shelf like illustrated on Figure 3.1.

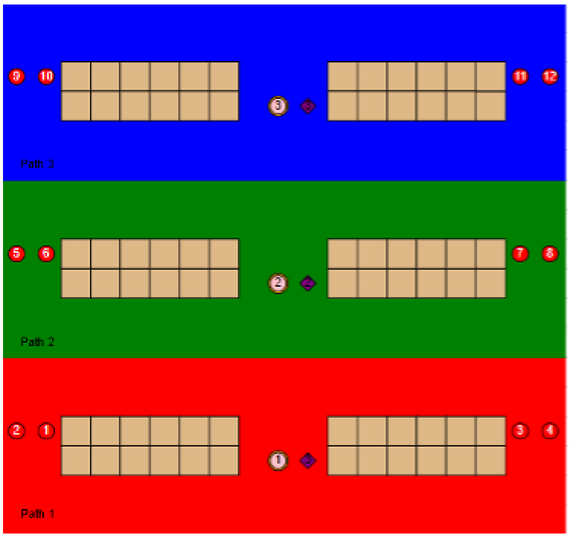


Figure 3.1: The Warehouse Layout

Red path illustrates predefined path for AGV shuttle numbered 1-2-3-4. Whereas green path illustrates predefined path for AGV shuttle numbered 5-6-7-8. Finally, blue path illustrates predefined path for AGV shuttle numbered 9-10-11-12. There are 3 dropping off and 3 charging points for 12 total at the warehouse. For AGV scenario robots were able to use just charging points and drop-off that they are on their zone. However, for AMR and ACMR shuttles they were independent to use any of them.

3.2 Mathematical Model

The central objective of this study is to initiate a mathematical model that would enhance the parameters determined by Python which include cost, travel distance, and speed of order fulfilment amongst other Key Performance Indicators. The model seeks to establish an optimal deployment configuration for AGV, AMR and ACMRs in consideration of real-world warehouse structure.

The aim of this research will be to achieve a mathematical model which will optimize the deployment of ACMR, AGV, and AMR in a warehouse. As well as at the end there will be comparison analysis for those robots. This model seeks to reduce the operational cost by minimizing travel time, energy consumption and waiting time while still addressing the need to wait for recharging and maintenance.

In case of the warehouse system, a large portion of the cost can be reduced due to the optimization of the robot's movement, order picking, and recharging process. This mathematical model that will be presented in this study will also be utilizing Python for optimal solutions of mathematic programming models.

3.2.1 Objective Function

The primary focus of the warehouse and its operations, which involves the execution of the Task, is best captured by the objective function as it seeks to optimize the overall operating operational cost which is Z. Among these can be listed as travel time, energy usage and total travel distance. Aggregating these factors the function guarantees optimal cost-effective distribution of robots within the warehouse. The objective function is represented mathematically as such:

$$\min Z = \sum_{i \in R} \alpha_{\tau(i)} \sum_{t \in T} x_{i,t} \cdot d_{i,t} + \sum_{i \in R} \beta_{\tau(i)} \sum_{t \in T} x_{i,t} \left(t_{i,t} + T'_{i,t} + P_{\tau(i)} + D_{\tau(i)} + H_{\tau(i)} \right) + \sum_{i \in R} \gamma_{\tau(i)} \cdot E_i$$

1. **Total Operational Cost (Z):** Z is the operation-related cost of the warehouse using ACMRs, covering travel distance, energy consumption, and total time. The unit of Z is monetary—usually dollars or euros. To evaluate this cost, the different components of time, energy, and distance are transformed into monetary costs using appropriate weights (α, β, γ) that reflect their financial impact. Lower operating costs are achieved by eliminating unnecessary physical effort, reducing energy expenditures, and minimizing waiting times, thereby increasing overall efficiency. Minimizing delays implies that robots can perform more tasks within a particular period.Higher customer satisfaction Engagement of completing orders quicker which means faster delivery.

2. **Travel Distance (D_i):**
$$\sum_{i \in R} \alpha_{\tau(i)} \sum_{t \in T} x_{i,t} \cdot d_{i,t} = D_i, \quad \forall i \in R, \forall t \in T$$
The total time spent by each robot i while traveling between various locations to complete its assigned tasks $t \in T$. The binary decision variable $x_{i,t}$ equals 1 if

Table 3.1: Notation and Definitions

Symbol	Type / Domain	Description
D_i	$D_i \geq 0$	Continuous decision variable representing the total travel distance of robot i across all assigned tasks.
$x_{i,t}$	$x_{i,t} \in \{0, 1\}$	Binary decison variable, 1 if robot i is assigned to task t, 0 otherwise.
$d_{i,t}$	$d_{i,t} \geq 0$	Distance required for robot i to execute task t (contributes to D_i).
$t_{i,t}$	$t_{i,t} \geq 0$	Time taken for robot i to reach task t.
$T'_{i,t}$	$T'_{i,t} \geq 0$	Additional travel time based on shuttle type.
$T'_{i,t} = \begin{cases} 2T_t, & \text{if } i \text{ is an AGV shuttle} \\ T_t, & \text{if } i \text{ is an AMR or ACMR shuttle} \end{cases}$		
$P_{\tau(i)}$	Parameter	Pick-up time based on shuttle type.
$D_{\tau(i)}$	Parameter	Drop-off time based on shuttle type.
$H_{\tau(i)}$	Parameter	Handling cost (only for AGV shuttles).
E_i	$E_i \geq 0$	Total energy consumed by robot i (Watt-hours).
$\alpha_{\tau(i)}$	Parameter	Weight for travel distance minimization.
$\beta_{\tau(i)}$	Parameter	Weight for task execution time minimization.
$\gamma_{\tau(i)}$	Parameter	Weight for energy minimization.

robot i is assigned to task t, and 0 otherwise. The individual travel time for task t by the robot i is $d_{i,t}$ contributes the total travel distance D_i.Measured in meters. Reducing travel time allows robots to complete more tasks in a given period, that is why overall efficiency increased.

3. **Energy Consumption (E_i):**

$$\sum_{i \in R} \gamma_{\tau(i)} \cdot E_i$$

This constraint specifies the total energy consumed by robot i. This energy consumption constraint includes energy consumed when moving between locations and carrying tasks Measured in Watt-hours (Wh).Lower energy consumption saves resources; promotes sustainable use of energy; and, most importantly, reduces downtime for recharging.

4. **Total Time:**

$$\sum_{i \in R} \beta_{\tau(i)} \sum_{t \in T} x_{i,t} \left(t_{i,t} + T'_{i,t} + P_{\tau(i)} + D_{\tau(i)} + H_{\tau(i)} \right)$$

The total distance spent by each robot i while traveling between various locations to complete its tasks $t \in T$. which includes travel time $t_{i,t}$, additional shuttle-based travel time $T'_{i,t}$, predefined pick-up time $P_{\tau(i)}$, drop-off time $D_{\tau(i)}$, and handling cost time $H_{\tau(i)}$. Time is measured in minutes. The minimization of this waiting time will help to utilize the robot optimally because it spends less time in idleness thereby gaining a lot of productivity.

5. **Monetary Cost Representation:**

   Each element is given weightage with a proper factor to make the terms comparable and consistent with the operational objectives of the warehouse in the development of the objective function such as α described as weight assigned to the total travel distance (D_i).Whereas, β was described as weight assigned to the cost of total spend time and finally γ was described as weight assigned to the total amount of energy consumption (E_i). By transforming these into a common monetary form (e.g., dollars or euros), they contribute to a unified cost function that represents overall operational cost (Z) in monetary terms.

3.2.2 Sets & Indices

Sets and Indices used in the mathematical model shown on Table 3.2 and Table 3.3

Table 3.2: Sets Used in the Model

Set	Description
R	Set of robots, $R = \{1, 2, \ldots, n\}$. This defined set monitors the presence of robots on the ground. Each $i \in R$ represents an individual robot. Robot shuttles are classified as AGV, AMR, and ACMR.
T	Set of tasks, $T = \{1, 2, \ldots, q\}$. Tasks are assigned to robots for execution. Each $t \in T$ is a specific task. ACMRs can perform multiple tasks simultaneously.
L	Set of storage locations, $L = \{(1, 2), (1, 3), \ldots, (m, n)\}$. Locations containing items for picking. Each $l \in L$ represents a storage point. Task selection is based on a Poisson distribution.
P	Set of paths or aisles, $P = \{1, 2, \ldots, p\}$. Used only by AGV shuttles requiring predefined paths. Each $p \in P$ represents a warehouse path or aisle.
H	Set of drop-off points, $H = \{1, 2, \ldots, o\}$. Locations where goods are delivered or picked. Each $h \in H$ is a drop-off point.
S	Set of charging stations, $S = \{1, 2, \ldots, c\}$. Charging stations maintain robot battery levels. Each $s \in S$ is a designated charging location.

Table 3.3: Indices Used in the Model

Index	Description
i	Index representing robots, where $i \in R$.
t	Index representing tasks, where $t \in T$.
l	Index representing storage locations, where $l \in L$.
p	Index representing paths or aisles, where $p \in P$.
h	Index representing drop-off points, where $h \in H$.
s	Index representing charging stations, where $s \in S$.

3.2.3 Decision Variables

Decision Variables used in model showed in Table 3.4.

Table 3.4: Decision Variables Used in the Model

Variable	Type	Description
$x_{i,t}$	Binary	Equals 1 if robot i is assigned to task t, and 0 otherwise.
pickup_time$_{i,t}$	Continuous	Time at which robot i picks up task t. Used to schedule task start times and align with task arrivals.
dropoff_time$_{i,t}$	Continuous	Time at which robot i completes task t, including travel and processing durations.
assignment_time$_{i,t}$	Continuous	Time when task t is assigned to robot i. Used for sequencing to avoid task overlap.
E_i	Continuous (Watt-hours)	Total energy consumed by robot i for all assigned tasks.
$d_{i,t}$	Continuous (Meters)	Travel distance required for robot i to execute task t, contributing to total distance D_i.
Makespan	Continuous (Time)	Represents the overall completion time of all tasks, including delays.
needs_charge	Binary	Indicates whether robot i requires recharging before proceeding with new tasks.
charge_start$_i$	Continuous (Time)	Time at which robot i starts recharging. No tasks are assigned during this phase.
charge_end$_i$	Continuous (Time)	Time at which robot i completes recharging. Tasks resume after this time.

3.2.4 Parameters

Parameters were decided as follows and shown Table 3.5 for the mathematical model.

Table 3.5: Model Parameters and Descriptions

Parameter	**Type / Unit**	**Description**
B_{max}	Watt-hours (Wh)	Maximum battery capacity of a robot. Ensures robots can complete tasks without interruption. All robots begin tasks with this energy level.
$B_{\text{min\_threshold}}$	Watt-hours (Wh)	Minimum battery level threshold indicating when a robot needs to recharge. Ensures robots return to charging stations before battery depletion.
$P_{\tau(i)}$	Time (minutes)	Predefined pick-up time parameter, varying with shuttle type. Proportional to real-time values.
$D_{\tau(i)}$	Time (minutes)	Predefined drop-off time parameter, varying with shuttle type. Proportional to real-time values.
$H_{\tau(i)}$	Time (minutes)	Predefined handling cost time, applicable only to AGV shuttles. Proportional to real-time values.
λ	Tasks/minute	Poisson task arrival rate. Models randomness of task arrivals in dynamic scheduling.
α, β, γ	Cost Weights	Cost weights for distance, time, and energy in the objective function based on shuttle type. Unified into monetary cost units (e.g., dollars/euros).
Speed(i)	m/s	Average speed of robot i. Used to determine travel duration.
Energy_per_meter(i)	kWh/m	Average energy consumed per meter of travel for robot i.
Recharge_time(i)	Time (minutes)	Time needed to fully recharge robot i from 0 to B_{max}. If half-charged, time is halved.
Payload_capacity(i)	Tasks	Maximum number of tasks robot i can carry. 1 for AGV/AMR; more than 1 for ACMR.
$d_{i,t}$	Meters	Distance required for robot i to perform task t. Constant in the model after computation.
$d_{\text{inter}}(t, t')$	Meters	Distance between drop-off location of task t and pickup of next task t'. Constant in the model after computation.
task_arrival_time$_t$	Time (minutes)	Arrival time of task t, modeled using a Poisson process.
M	Large Constant	Big-M constant used to enforce logical constraints.

3.2.5 Constraints

The model presents several constraints to enable efficient robot operations and account for the limitations of a real warehouse environment. All constraints are implemented in the Python modeling environment.

1. **Task Exclusivity & Assignment:**

$$\sum_{i \in R} x_{i,t} = 1, \quad \forall t \in T$$

Each task t must be assigned to exactly one robot i, ensuring no task is omitted or duplicated. This optimizes task distribution and prevents multiple robots from performing the same task.

2. **Payload Capacity:**

$$\sum_{t \in T} x_{i,t} \leq \text{Payload\_capacity}(i), \quad \forall i \in R$$

Each robot i can only carry a number of tasks less than or equal to its payload capacity. For example, AGV and AMR have a capacity of 1, while ACMRs may carry multiple tasks.

3. **Robot-Specific Task Assignment:**

$$x_{i,t} = 0, \quad \forall i \in R_{\text{AGV}}, \text{ if dynamic rerouting is required}$$

AGV robots cannot be assigned tasks requiring dynamic rerouting due to their dependency on predefined paths.

4. **Energy Consumption Constraint:**

$$\sum_{t \in T} x_{i,t} \cdot d_{i,t} \cdot \text{Energy\_per\_meter}(i) \leq B_{\text{max}}, \quad \forall i \in R$$

Total energy used by robot i must not exceed its maximum battery capacity B_{max}.

5. **Recharge Trigger Constraint:**

$$E_i^{\text{remaining}} = B_{\text{max}} - \sum_{t \in T} x_{i,t} \cdot d_{i,t} \cdot \text{Energy\_per\_meter}(i)$$

$$E_i^{\text{remaining}} \geq B_{\text{min\_threshold}} - M \cdot \text{needs\_charge}(i), \quad \forall i \in R$$

If remaining energy falls below $B_{\text{min\_threshold}}$, then needs_charge(i) becomes 1, enforced using Big-M.

6. **Task Assignment Optimization with Poisson Arrivals:**

$$\lambda_t = \text{Poisson rate of task arrivals}, \quad \forall t \in T$$

$$P(k) = \frac{\lambda^k e^{-\lambda}}{k!}, \quad k \in \mathbb{N}$$

Poisson distribution models real-world task arrival randomness; parameters such as λ are defined at the beginning of the model (e.g., 5 tasks per 60 seconds).

7. **Pickup Time Constraint:**

$$\text{pickup\_time}_{i,t} \geq \text{task\_arrival\_time}_t, \quad \forall i \in R, \forall t \in T$$

A robot cannot start picking a task before it has arrived.

8. **Drop-off Time Constraint:**

$$\text{dropoff\_time}_{i,t} \geq \text{pickup\_time}_{i,t} + \frac{d_{i,t}}{\text{Speed}(i)} + T'_{i,t} + P_{\tau(i)} + D_{\tau(i)} + H_{\tau(i)}, \quad \forall i \in R, \forall t \in T$$

   Drop-off time includes all relevant times for a complete task cycle.

9. **Sequential Task Scheduling Constraint:**

$$\text{assignment\_time}_{i,t'} \geq \text{dropoff\_time}_{i,t} + \frac{d_{\text{inter}}(t,t')}{\text{Speed}(i)}, \quad \forall i \in R, \forall t, t' \in T$$

   Tasks must be scheduled sequentially with travel time between tasks accounted for.

10. **Recharge Scheduling Constraint:**

$$\text{pickup\_time}_{i,t} \geq \text{charge\_end}_i - M \cdot (1 - \text{needs\_charge}(i)), \quad \forall i \in R, \forall t \in T$$

   If recharge is needed, task pickup can only start after charging is completed.

11. **Recharge Duration Constraint:**

$$\text{charge\_end}_i \geq \text{charge\_start}_i + \text{Recharge\_time}(i) \cdot \text{needs\_charge}(i), \quad \forall i \in R$$

   Recharge must last at least the required time depending on the energy level of the robot.

12. **Makespan Constraint:**

$$\text{makespan} \geq \text{dropoff\_time}_{i,t}, \quad \forall i \in R, \forall t \in T$$

   Ensures that makespan captures the total completion time of all tasks.

13. **Binary and Non-Negativity Conditions:**

$$x_{i,t}, \ \text{needs\_charge}(i) \in \{0, 1\}$$

$$\text{pickup\_time}_{i,t}, \ \text{dropoff\_time}_{i,t}, \ E_i, \ \text{charge\_start}_i, \ \text{charge\_end}_i, \ \text{makespan} \geq 0$$

   These conditions ensure logical feasibility, preventing negative values and enforcing binary choices in the model.

4 Results

4.1 Introduction

This chapter presents the in-depth modeling and simulation outcomes and optimization for AGVs, AMRs, and ACMR shuttles in a warehouse systems. The analysis is intended to offer insight into the performance of each robot during similar warehouse and task generation scenarios. By standardizing warehouse environments and maintaining constant patterns of task demand, the study makes the strengths and weaknesses of each robotic system very clear vis–vis one another for fair and transparent assessment.

The outcomes presented in this chapter are obtained from simulations implemented across different scenarios-tasks have Poisson distributions regarding intensity level. Using IBM CPLEX as the solver, the mathematical models capture the dynamics of real-world warehouse operations, from tasks assignment to robot movements and then to charging behavior and energy consumption. For performance metrics after optimization, elaborate simulation frameworks were developed in Python, which provide time-index tracking of all activities of the robot with their energy status, path planning, and operation delays.

One of the key aspects of this analysis is the the emphasis on performance indicators that goes beyond task assignment efficiency. For that reason, measures such as total time of completion, travel distance, energy consumption, and robot utilization are used in determining operational effectiveness. Robot utilization efficiency is visualized with stacked bar graphs illustrating the percentages of time that each robot spends executing tasks, traveling, charging, and idling. These breakdowns are important for identifying under-utilization or operational bottlenecks within each robotic system.

Another element related primarily to this chapter is how the values of the objective function change with respect to the increase of the intensity of tasks. Scatter plot of the number of generated tasks versus the corresponding objective function values indicates the scalability and resource responsiveness of each of the robot types. It further lends itself to direct cost comparisons and operational sustainability among AGVs, AMRs, and ACMR configurations as the volumes of tasks increase.

In particular, ACMR systems outperform AMR and AGV performances in terms of average task completion time and resource utilization. The ability to handle multiple cases and the vertical navigation logic integrated into the ACMR system designs have greatly reduced both travel distance and total time, contributing to substantial energy and throughput gains. On the contrary, being constrained by a fixed path with a shelf-return requirement, AGVs show quite high idle times, long travel distance and energy consumption as a reflection of their stiffness and constraints typical of guided shuttle systems like AGVs. The task density handling and energy efficiency of ACMRs is ahead of even AMRs, AGVs like expected.

The comparative visualizations and summary tables of KPIs presented in this chapter articulate all these differences, thus supporting the premise that ACMRs will provide a better scalable and adaptable solution in high-density warehouse operations. In the following sections, each type of robot is presented in detail, along with simulation outputs, performance trends, and interpretation of findings that support the main aim of the research.

4.2 Task Assignment Trends & Objective Function Analysis

It was very crucial to study how these systems differ in terms of responses to increasing task volumes; determining their scalability and operational efficiency will be strengthened by it. Trends in the objective function values of AGV, AMR, and ACMR systems, depending on the number of tasks generated, are analyzed on simulation outputs averaged over 100 cycles per robot type. This objective function is a compound measure of total travel distance, task completion time (makespan), and energy consumption, providing a more comprehensive measure of system performance.

The task generation was done using Poisson processes across all simulations to simulate the stochastic nature of scaled real-world task arrivals in typical warehouse environments; as a result, the generation of tasks made with Poisson function such; if a task would be generated at the 5th second, then the assigned robot would have to wait until 5th second to go toward the task, thus, introducing operational delays that would be more realistic. It is important as a temporal dynamic in the interpretation of simulation results, providing a more realistic evaluative framework compared to static task generation.

The results show that for AGV systems, the values of the objective function in general tend to increase monotonically with the volume of tasks. This is a natural expectation, considering the rigidity and path-dependence of AGV navigation. With increasing numbers of tasks, increasing congestion on routes, longer detours, and greater energy requirements become evident for AGVs. They are not able to optimally adjust dynamically to the changing distribution of work because they lack decentralized path planning. The plotted results give evidence of this linear gain, indicating scalability limits of AGV shuttle applications particularly under dense task environments.

Thus, the AMRs, thanks to their flexibility in moving their tasks assigning dynamically to the robots in real-time, show a milder decrease in objective values within increased task loads. These qualities make them efficient on the whole under the stressful rising workloads compared to AGVs. Decentralized decision-making real-time rerouting and efficient opportunistic management of their energy have been schemed to enable such behaviour. However, the system still suffers gradual declines in performance due to increasing travel distances and localized congestion with improving energy constraints as the number of tasks increases. The results, being smooth in trend, indicate much better flexibility but still point out limits under heavier loads.

ACMRs, on the other hand, are consistently the best performers for average objective function values against AGVs and AMRs. Unlike other shuttle systems, their trend is not perfectly monotonic. Instead, the objective course has very minor fluctuations at different task volumes, even when they all use the same modeling assumptions and code structure in all the simulations.

This phenomenon is not an exception but an emergent feature of these systems being the architecture of ACMR and task logic, and is very pronounced in environments having multi-pick, multi-drop capability. The main possible reasons for such fluctuations can be described as:

Task Consolidation Variability: ACMRs can group a large number of tasks into a single haul, which is why they are extremely efficient; however, the effectiveness of this consolidation depends on the spatial and temporal distribution across which those tasks occur. Some simulation runs may be highly effective at grouping tasks, while others may achieve far less effective pairing, thus influencing total distance traveled and energy consumed.

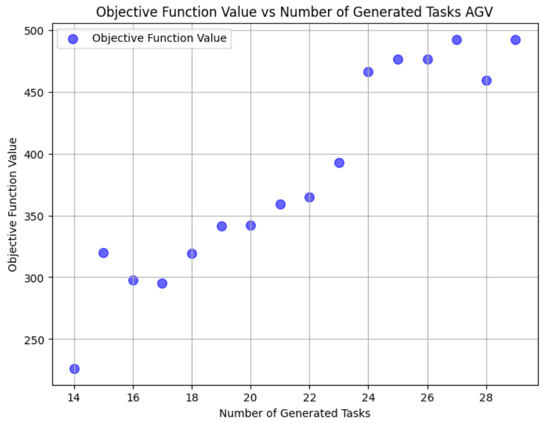
Drop-off and Pickup Interleaving: As ACMR currently executes multiple cases per cycle, the combination of pick-up and drop-off points accounts for complex routing dependencies. Small modifications to task locations or arrival times affect the efficiency of the resulting routes significantly.

Time-Indexed Task Start Constraints: However, due to the Poisson-based task generation, tasks coming in may not be the best timed for example, after a robot has started running its route. In such cases, even though the robot may haul more items, it does not turn back or wait for long periods without damaging its overall path efficiency.

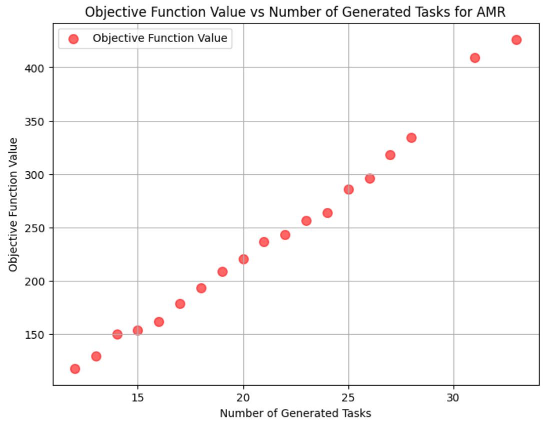
Real-World Operational Delays: This model accurately accounts for waiting, charging, and scheduled routes and therefore has even increased the rereadability of the objective function to minor changes in task arrival sequences-systems such as ACMRs which are more tightly optimized take on the burden.

Importantly, such variations fall within the normal behaviour of ACMRs, themselves not the limitations of the model or the simulation code. ACMRs, on average, deliver significantly more reduced total cost, energy consumption, and completion times, all of which indicate their excellent scalability. Meanwhile, the fluctuations themselves reflect the subtlety of the high-density multi-task systems: indeed, a strength of ACMRs that allows them to exceed the performance of rigid architectures, even if the outcome of individual cycles varies a little because of the grouping pattern of tasks used.

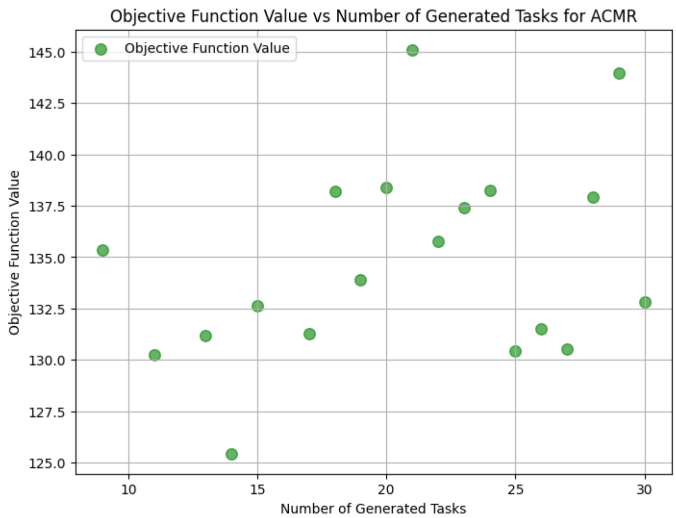
As seen from the Figure 4.1, the respective scatter plot of Objective Function Value vs Number of Generated Tasks clearly captures these patterns-higher sharp ascent for AGVs, a smoother yet still increasing curve for AMRs, and tightly clustered but non-linear trend for ACMRs, reflecting their efficiency and adaptive performance.



(a) AGV: Objective Function vs Task Count



(b) AMR: Objective Function vs Task Count



(c) ACMR: Objective Function vs Task Count

Figure 4.1: Comparison of Objective Function Value Trends for AGV, AMR, and ACMR with Increasing Task Volume

4.3 Utilization Efficiency

Robot utilization efficiency can be evaluated as a contrasting lens in the operational effectivity of any warehouse automation system. Time spent by each robot in the time slice execution, travel, charging, and idle states reflects the performance of a robot and latent inefficiency concerning throughput and cost-effectiveness.

These dynamics are shown in the comparative stacked bar charts of AGV, AMR, and

ACMR robots at Figure 4.2, Figure 4.3 and Figure 4.4. These figures show how 12 robot of the system spent their time during task assignment in the simulation. Notably, all of the charts have uniform styling for great clarity, employing specific colours for Task Time (pink), Travel Time (orange), Charging Time (green), and Idle Time (blue). That way, an easy comparison among the three systems is made.

For the AGV utilization chart, despite taking task time as a significant component of robot activity, a big percentage of time is still accrued under travel and idle states. This is mainly due to the AGVs' fixed-path navigation model, such that each robot must follow pre-defined routes and return to the depot after finishing each task. The multiple return trips coupled with the loading and shelving delays brought by workers inflate the overall operational time. Charging time, though visible, is relatively less because of the controlled routing and limited energy depletion in each cycle.

AMR utilization charts show a greater amount of idle time, exceeding in some cases 60%. This is a result of a decentralized task assigning model and a direct pick-drop workflow, which incur flexibility but leave some AMRs idle when density of tasks or spatial proximity is poor. Further, AMRs tend to cover longer distances with every task due to dynamic navigation, as is seen with time of travel distribution.

Designed for a high density, multi-level environment, ACMR robots create a far more balanced efficient time allocation profile between robots. Due to the fact that task time per robot reflected the multi-pick ability of robots, fewer trips were made for a task batch. ACMR robots also have quite moderate high idle time, somewhat surprising, given their advanced task-handling logic. Two main reasons explain the phenomenon. First, tasks are created randomly (with the use of the Poisson distribution); that is, the arrivals are stochastic and unevenly spaced. Therefore, the robots cannot pick up anything until a task actually exists in the system, for example at the 5th second, a task could not be taken care of before 5th second as it was created only after that time. Thus, a natural buffer into idleness is created, wherein the second aspect states that, although there exists multitasking in the model, distance-based travel time and space spread still determine robot engagement and hence create localized idleness despite being high-tenacity robots.

It may be noted finally that ACMRs have the most task-oriented supported utilization behavior, with efficient balance between internal throughput and charging logic, while AGVs have high structural delays due to path rigidity, and de-centralization is a challenge for AMRs in managing idle time although very flexible. These findings are very important informing future designs of robotic warehouse operational deployment since the most appropriate automation model selection goes beyond navigation logic or energy efficiency into how effectively robots use their active time in a real-world operational tempo.

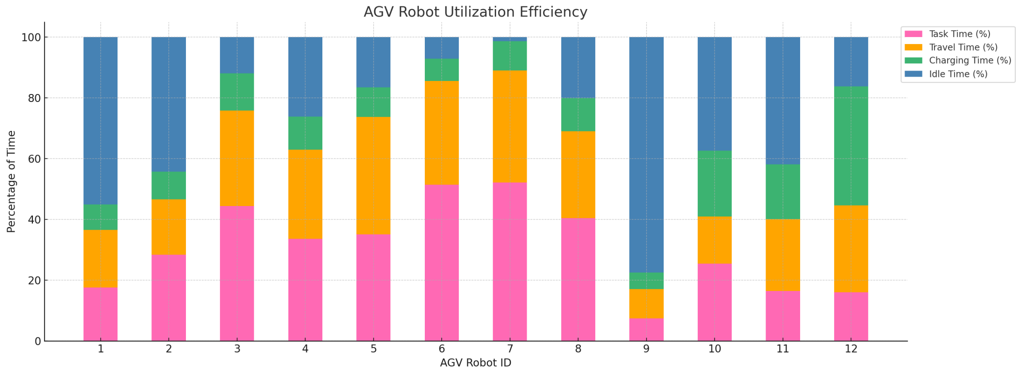


Figure 4.2: AGV Robot Utilization Efficiency

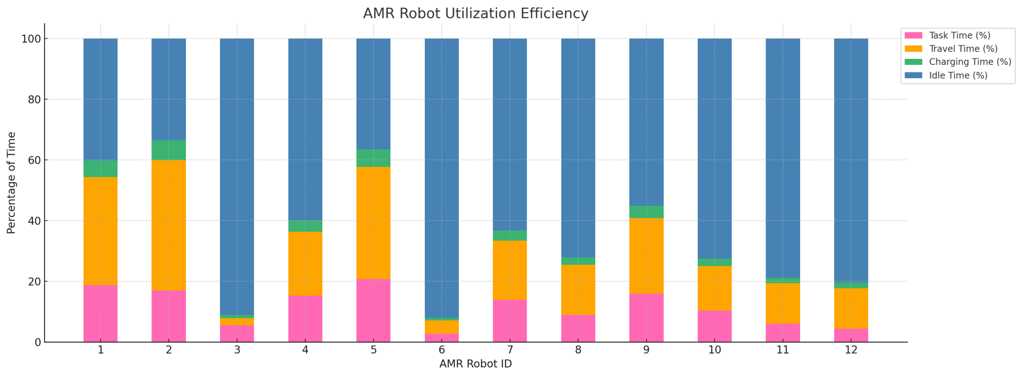


Figure 4.3: AMR Robot Utilization Efficiency

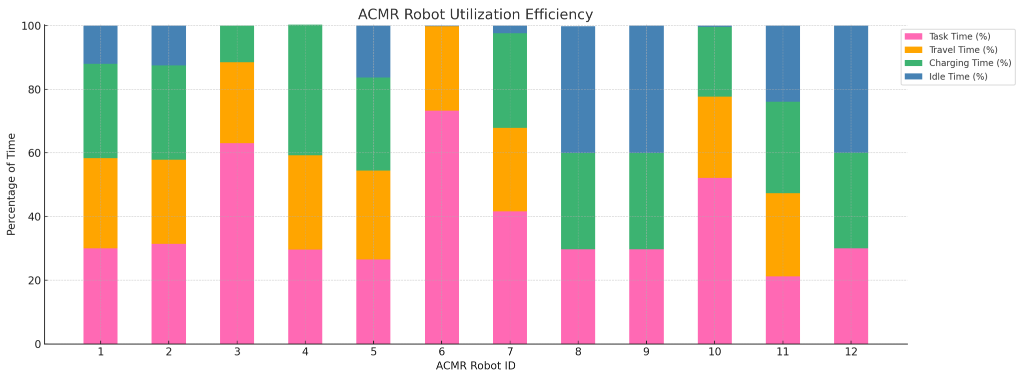


Figure 4.4: ACMR Robot Utilization Efficiency

4.4 Energy Consumption & Travel Distance Analysis

The energy consumption and travel distance per task were assessed according to three robotic shuttle systems: AGVs, AMRs, and ACMRs, graph illustrates the the average of 100 different task assignment under controlled conditions with a Poisson task generation rate fixed at 20 and simulation rate was 100. A comparative view is captured by Figure 4.5 in the form of a split dual-axis bar chart on which energy consumption (kWh) and travel distance (units) per task are shown together. Energy measurements are plotted against the left y-axis while travel distances are rendered against the right y-axis, providing a succinct two-way view of system efficiency.

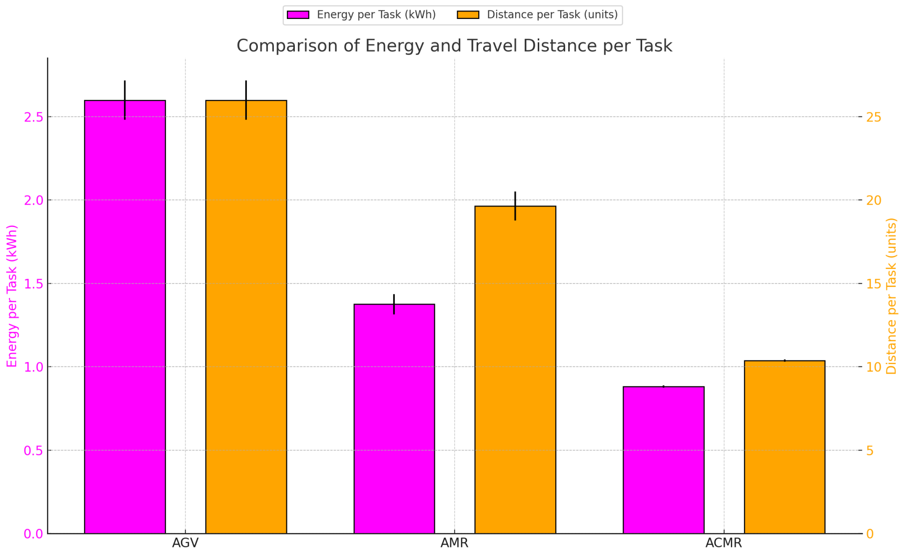


Figure 4.5: Comparison of Energy & Travel Distance per task across AGV, AMR, and ACMR shuttles based on 100 simulations

The comparative analysis has made as illustrated in Figure 4.5 which shows the notable differences in different AGV, AMR, and ACMR systems in reference to energy consumption per task and travel distance per task. ACMR has shown reduction on energy consumption per task. As it has consumed 35.81% less as compared to AMR and more than 65.85% when compared with AGV , making it the most energy-efficient system among those used in the study. In addition, average travel distance per task, when compared with AMR, was found to be lower by 47.16% and lower by more than 59.81% when compared with AGVs, indicating better routing accuracy and task consolidation efficiency.

The error bars express the variation (min–max range) throughout runs of 100 simulations, on the graph, it further shows high consistency and stability with which ACMR performs as compared to AGV and AMR systems, with little tendency for fluctuation. Such information portrays the scalability and operational efficiency of ACMRs in high-density warehouse environments where energy and travel costs need to be minimized for long-term throughput and productivity.

Navigating away from the observations drawn from the chart, AGVs consume the most energy and traverse the longest distance per task as expected from their operating paradigm. As shelf-to-person systems (e.g., Quicktron), AGVs not only move shelves to worker stations but also return them after each task to their original place. This fixed-path bidirectional movement inflates the surrogate distance and energy consumed per task, albeit in a centralized arrangement.

AMRs are quite an improvement as they behave like decentralized navigation systems, in such a way they make Harmon on the projects, when energy and distance numbers are not bad. They can reach directly from point A to point B to drop off the item without moving the shelf. The energy consumption adds up due to circuitous route travelling and decentralized map navigation, notwithstanding the structured lightweight and high-maneuverability design features of AMR.

With inspiration drawn from Hai Robotics A42 case-handling robots, the ACMRs maintain consistent minimum energy and distance metrics per task. Compact routes with little idle movement are achieved due to intense picking capabilities and multi-task handling efficacy. They optimize task sequences and often consolidate multiple items into one single run, further lowering energy expenditure and travel requirements.

In conclusion, this study substantiates the assertion that ACMRs are the most energy efficient and travel-efficient, followed by AMRs, with AGVs coming in last because of their fixed structure in return routing. This is of paramount relevance when warehouse operations would be centred in the sustainability paradigm whilst also having high-throughput performance and functional efficiency at the least cost.

4.5 Task Completion Time Analysis

Average task completion time is one of the more important metrics indicative of operational efficiency in robotic warehouse systems as weighted 0.5 in the objective function. It asserts the velocity with which such a system can execute a customer order or some internal logistics action under varied loads and circumstances.

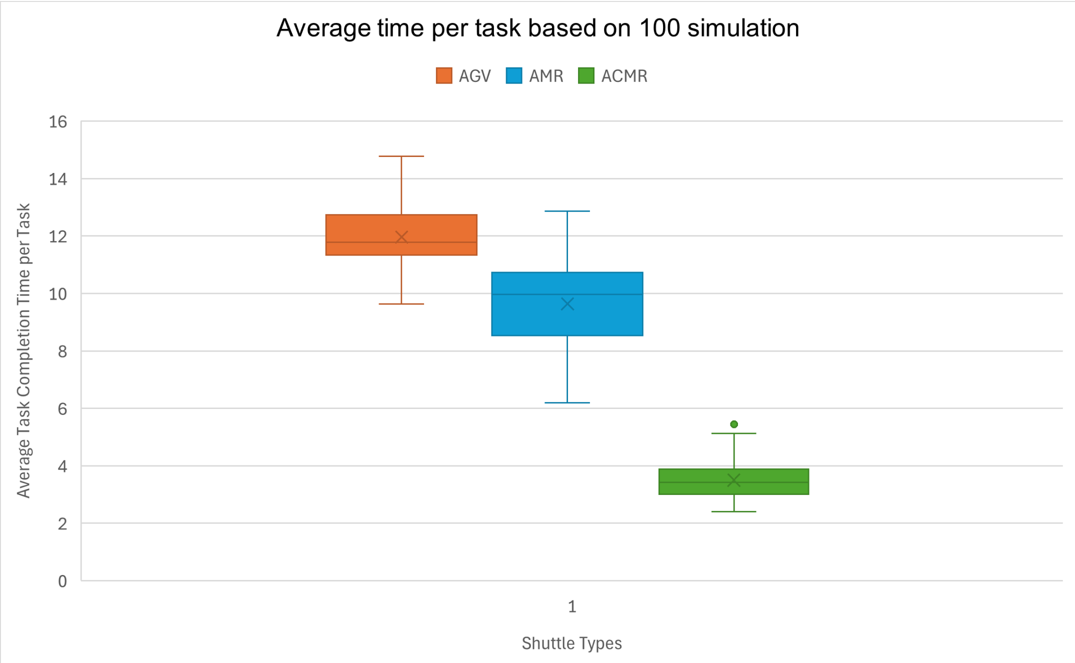


Figure 4.6: Comparison of Average Task Completion Time per Robot Type based on 100 simulations.

Figure 4.6 shows the box plot comparing the average task timings during completion under AGV (Quicktron Shelf-to-Person), AMR (InVia Picker), and ACMR (Hai Robotics A42) systems. Each box plot is created based on 100 simulation cycles and hence is a good measure of variability and the distribution of task performances under Poisson task arrivals. As can be seen from Figure 4.6, ACMRs had an edge over AGVs and AMRs in all of the tests with an average task completion time of only 3.50 second, which is around 70.74% faster than AGVs with an average of 11.97 seconds and 63.70% faster than AMRs with an average of 9.64 seconds. Conclusively, AMRs were 19.41% faster in completing tasks than AGVs.

These performance differences could be explained due to the operational mechanism for each system. AGVs used the shelf-to-person working model; thus, the robot has to carry the shelf to the workstation and then bring it back to storage after task completion—all this traveling, resulting in a longer time per task. In contrast, AMRs have a more direct method of working, supporting goods-to-person with no requirement for shelf return, hence shortening task cycles. ACMRs seek to maximize systems' efficiency through multi-pick and multi-drop functions so that every robot could carry multiple cases or multi-tasks in one trip. This double optimization cuts both travel and idle time to provide the shortest task completion times among the three.

ACMRs show very low task completion times, with most clustered around 3-4 seconds. This basically shows the high-density picking capabilities and precision pathing of ACMRs, which are specially designed for fast multi-level case handling. The lack of spread and tight quartile distribution further implies that they do indeed provide stable operations, even under varying task loads.

On the other side, AMRs show lack of consistency among completion times. Much larger interquartile range, with a few outliers, show greater variability than AMRs' completion times. This variability is because AMRs rely on decentralized navigation and dynamic obstacle avoidance in real-time. But still, AMR shuttles provide more flexible navigation than AGV shuttles. While being highly consistent, AGVs don't move that fast compared to AMRs or ACMR. The fixed routes and sequential shelf transport mechanisms increase the time it takes for completing tasks. Their standard range of distribution is narrow and hence, predictable in performance, though at a cost of time.

This comparison clearly strengthens the argument of superiority of ACMRs when it comes to efficiency in high-density fulfillment environments. Additionally, the speed and stability offered by ACMRs also minimize waiting time and thus increase the throughput in every cycle, which is critical for scalable warehouse automation.

4.6 Discussion & insights

As critical insights from the comparative analysis of AGV, AMR, and ACMR systems conducted in this study emerge concerning their operational behavior and trade-offs in performance under varying warehouse task densities.The performance indicators for the AGV (Quicktron Shelf-to-Person), AMR (InVia Picker), and ACMR (Hai Robotics A42) systems are summed up in Table 4.1 of this thesis. It highlights the critical performance metrics such as completion time, travel distance, and energy expenses. The values depicted are statistical summaries derived from 100 simulation cycles run under the Poisson task arrival settings. The relative improvement was greatest for ACMRs in all the evaluation criteria. The total system completion time for ACMRs is 137.46 seconds, as opposed to 386.14 seconds for AMRs and 490.66 seconds for AGVs. On a per-task basis, ACMRs completed a task in an average time of 3.50 seconds-approximately 70.74% faster than AGVs (11.97 seconds) and 63.70% faster than AMRs (9.64 seconds).

In terms of travel distance efficiency, the average distance traveled by ACMRs per task is the shortest at 10.38 meters, 59.81% lesser than that of AGVs (25.81 meters) and 47.16% less than AMRs (19.62 meters). This performance edge is due to multi-pick and multi-drop capabilities, enabling the merging of multiple operations into one single route. Unlike AGVs, which run on a shelf-to-person mechanism that takes more time and distance to return to the shelf after performing the operation, thus increasing the average travel and task times.

For energy analysis, scaled values based on real-time operational data were applied in a friendly simulation approach, wherein energy consumed per meter was assumed as 1.00 kWh for AGVs, 0.07 kWh for AMRs, and 0.085 kWh for ACMRs respectively. The lowest energy usage per meter was for AMRs, whereas the lowest energy consumed per task was found to be for ACMRs at 0.88 kWh as against AMRs at 1.37 kWh and 2.58 kWh for AGVs. This is the resultant of shorter distances travelled and improved efficiency in performing tasks in ACMR systems.

Table 4.1: Key Performance Indicators (KPI) Summary across AGV, AMR, and ACMR Systems

Metric	**AGV**	**AMR**	**ACMR**
Completion Time (s)	490.66	386.14	137.46
Average Task Completion Time (s)	11.97	9.64	3.50
Travel Distance per Task (m)	25.81	19.62	10.38
Energy Consumption per meter(kWh)	1.00	0.07	0.085
Energy Consumption per Task (kWh)	2.58	1.37	0.88

By far, it has been found out that ACMR performs better than the rest on a variety of dimensions. With the multi-pick capabilities, high mobility, and autonomous decision-making, ACMRs speed up and become more energy-efficient in task accomplishment, especially in task-intensive situations. This is in terms of significantly lower energy and travel distance per task, as well as shorter completion times. Moreover, ACMRs consistently maintained moderate idle time and high utilization, indicating better task saturation and effective scheduling.

AMRs were more idle under high task load; although there is a certain flexibility in task allocation since it follows a decentralized allocation approach, it is adaptive but does not have the same co-ordination efficiency as ACMR, which has been identified with a route-optimized task allocation. On top of these, the energy consumed by AMRs per task was also seen to be higher than that consumed by ACMRs, and returns on the benefits it brings actually reduced as task density increased—mostly in conditions where the pros and cons of path congestion and recharging frequency became greater.

AGVs are the most predictable and structured system, yet still manage to be the least adaptive and energy efficient of all systems. Due to the fixed paths and shelf handling dependent on workers, task time and redundancy on travels are increased, disadvantageous especially for dynamic and high-throughput warehousing environments. However, the average task assignation trend and high path determinism are characteristic of them, which can prove very useful in low-complexity environments.

These findings seem to argue even more for the general common hypothesis that ACMRs are more scalable and energy efficient as well as more operationally robust from all results compared to their counterparts in an environment lacking any competition with much bulkier tasks needing rapid order fulfillment. The multiple simulations that were run over different Poisson task rates indeed further indicated that performance stability could be achieved with ACMR while AMR and AGV systems showed a much sharper drop in performance with increasing load.

5

Conclusions & Future Works

5.1 Conclusions

The essence of this thesis is to perform a general comparative analysis of three warehouse automation types: Automated Guided Vehicles (AGVs), Autonomous Mobile Robots (AMRs), and Autonomous Case-handling Mobile Robots (ACMRs). The AGVs and the AMRs have been widely studied in both academia and industry. The ACMRs, however, are still grossly underexplored in research, while they are currently gaining momentum in high-density warehouse operations worldwide.

One of the most remarkable difficulties experienced during this research has been the scarceness of academic literature specifically targeted at ACMRs. The literature mainly discusses general warehouse management, task allocation methods, or AGVs and AMRs. There has barely been any structured simulation-based or mathematical model research for the ACMR system, with the focus being primarily on their efficiency in utilization, energy dynamics, and performance under different task generation rates. Such a scarcity of literature presented incredible hurdles to the research but also distinguished the novelty of the present work.

This framework is thus provided in detail and Academic research setup and simulations are implemented, compared, and evaluated with the AGVs and AMR systems using standardized KPIs, including overall time completion, average time completion per task, distance travelled per task, and energy consumed per task. The results reinforce the benefits of ACMRs in scalable, energy-efficient, and expeditious task execution under conditions of increasing task demand. These findings validated the potential of ACMRs in modern warehouses, providing what is essentially one of the first comparative academic assessments of ACMRs.

In this way, this thesis makes considerable contributions to the academic body of knowledge by being among the first to elucidate on the objective comparative evaluation of ACMRs in simulated warehouse environments leveling the ground for future research and industrial application.

5.2 Future Work

In light of the insufficient past academic research on ACMRs, many more directions of future studies can be awaited:

Development of Advanced Multi-Robot Coordination Models: Future works may study advanced coordination strategies particularly for ACMRs under conditions of multi-level shelving and real-time demand fluctuation scenarios.

Hybrid Simulation and Optimization Approaches: It combines discrete-event simulation with reinforcement learning or adaptive optimization techniques that could bring forth an even better model of dynamic environments wherein the task arrivals are stochastic.

Extended comparative studies: Further future researches might evaluate cost versus benefit analyses, ROI metrics, and long-term operational sustainability of each robot type to supplement decision makers in warehouse automation planning.

Human-Robot Collaborative Research with the ACMR: Future studies may also explore how ACMRs would interact with human workers and how such systems may build an environment in which safety and productivity would be optimized for hybrid work.

This thesis is a first part of the gap that exists on ACMRs in academia, making a practical framework and performance insights that encourage further research on this very important but underrepresented field of warehouse automation.

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