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A Comprehensive Review of Order-Picking Routing Models for Pick-Support Automated Guided Vehicles

Mahaling Davangave[1], Murali Matcha[2]

[1]Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bengaluru.
[2]Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bengaluru.

***Corresponding Author E-mail: mahaling850@gmail.com**

ABSTRACT: In order to reduce energy footprint and logistics expenses in the highly competitive supply chain of today, warehouses are using Pick-Support Automated Guided Vehicles (PS-AGVs). The efficiency of the system as a whole is greatly influenced by routing choices that are closely related to order assignment, grouping, sequencing, and early management because PS-AGVs use the majority of their power during the travel and acceleration phases. In order to reduce travel distance and watt-hour consumption, integrated planning frameworks utilize traffic-aware routing algorithms. This study reviews current developments in energy-aware order-picking. According to a comparative synthesis, models that incorporate two or more of these planning layers achieve average throughput benefits of, reduce trip distance, and improve on-time delivery reliability over single-issue approaches. The analysis provides actionable advice, demonstrating how warehouse managers choose and combine planning aspects to match order changes and service-level targets. As a result, this work offers a comprehensive research basis as well as a useful guide for constructing effective, customer-focused energy-efficient PS-AGV order-picking systems.

Keywords: Pick-Support Automated Guided Vehicles, Warehouse Management Systems, Optimization, IoT, Order-Picking Routing

1. Introduction

In the era of smart logistics and automated warehousing, the role of order-picking routing models has become a foundational element in ensuring high-performance operations. As customer expectations shift toward faster deliveries and real-time order tracking, warehouses are under increasing pressure to fulfil orders with maximum speed and accuracy [1-2]. In modern warehousing and logistics operations, order picking is one of the most labour-intensive and cost-critical activities, accounting for up to 50% of warehouse operating costs. With the growing demand for faster, more accurate order fulfilment especially in e-commerce and high-throughput environments many facilities have turned to AGVs to automate and streamline the order-picking process [3-5]. These AGVs assist human pickers or operate autonomously to transport items, navigate storage areas, and optimize material flow. A crucial component of ensuring the efficiency of AGV-supported picking operations lies in the design and implementation of effective order-picking routing models. These models determine the most efficient paths AGVs should follow to collect items from storage locations and deliver them to packing or consolidation zones. Unlike traditional human-based picking, AGV routing must consider not only distance and speed but also factors like energy consumption, traffic management, vehicle dynamics, and real-time adaptability [5-7]. Various routing models have been developed to address these challenges, ranging from simple heuristic methods like S-shape and return routing, to advanced optimization approaches using genetic algorithms, dynamic programming, and real-time traffic-aware models [8]. Each model type offers trade-offs in terms of complexity, computational demand, scalability, and efficiency. Some focus on minimizing travel time, others on energy use, and some aim for a balance of both. As AGVs become more integrated with Warehouse Management Systems (WMS), Internet of Things (IoT) technologies, and Artificial Intelligence (AI), routing models continue to evolve to support dynamic, multi-objective optimization [9-10]. Without such models, AGVs would operate reactively or follow rigid, suboptimal paths leading to excessive travel, battery drain, traffic congestion, and missed delivery windows. A well-designed routing model ensures that every AGV trip is purposeful, energy-conscious, and aligned with overall warehouse priorities such as reducing fulfilment time or maximizing throughput [11]. The selection of the most appropriate routing model depends on warehouse layout, order profile, fleet size, and operational goals making it a critical area of study and development for automated warehousing solutions [12-13]. When selecting the best order-picking routing strategy for PS-AGVs, the ideal model depends on your warehouse goals, layout complexity, and system capabilities. However, further research explores the optimization impact of storage location assignment with different routing methods and consider changes in pickers' walking routes [14-15]. Therefore, analyzing the highest performance of order-picking routing models is required for pick-support AGVs was provided and addressed in this paper.

2. Review of Order-Picking Routing Models for AGVs

2.1 Discrete Order Picking

Discrete order picking is also called single-order picking refers to the process where each order is picked individually, one at a time, from start to finish. Discrete order picking for AGVs is a simple and direct method where each AGV is assigned to pick and deliver one customer order at a time. In this approach, the AGV receives a picking task, travels to the necessary storage locations to retrieve all items for that single order, and then delivers them to a designated packing or shipping area before returning to standby or charging. Process of discrete order picking is displayed in Figure 1.

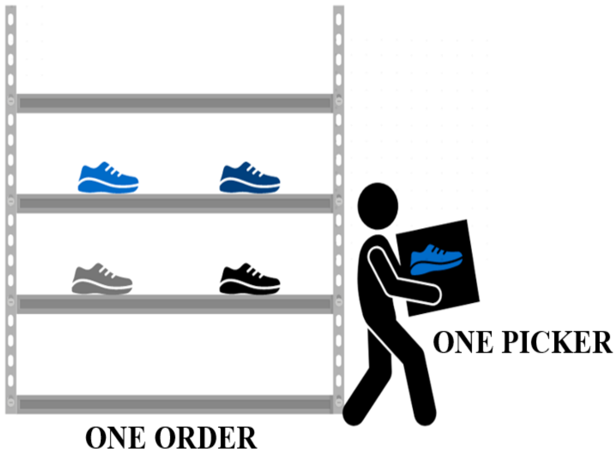

Figure 1: *Process of Discrete Order Picking*

This method is easy to implement and manage, making it particularly suitable for operations that require fast response times, such as e-commerce fulfilment centers handling urgent or high-priority orders. It eliminates the need for complex sorting or batching processes, reduces coordination overhead, and allows each AGV to operate independently with minimal traffic conflicts. Integrating dynamic routing, energy-aware path planning, and intelligent AGV dispatching helps enhance the performance of this approach. However, the main drawback is low efficiency AGVs often travel long distances with underutilized payloads, especially in warehouses with high order volumes or dispersed pick locations. The repetitive travel leads to increased energy consumption and wear on vehicles. Despite these limitations, discrete order picking remains effective in small to medium-sized warehouses, low-volume environments, or operations where real-time responsiveness is more critical than route optimization or efficiency [8].

2.2 Energy-Efficient Order Picking Routing

Energy-efficient order picking routing for AGVs focuses on minimizing energy consumption during the picking process by optimizing travel paths, reducing unnecessary movements, and managing vehicle acceleration and deceleration [17]. Unlike traditional methods that prioritize shortest distance or fastest route, energy-efficient routing considers factors such as smooth navigation, avoidance of congested or high-turn areas, and minimizing frequent stops and starts which are major contributors to battery drain in AGVs. This approach is particularly valuable in large or high-traffic warehouses where AGVs must operate continuously and manage limited battery capacity. By planning routes that are not only shorter but also smoother and less energy-intensive, warehouses extend AGV operating time between charges, reduce downtime for recharging, and lower overall energy costs.

Additionally, energy-efficient routing contributes to fleet longevity and better utilization of charging infrastructure. When integrated with intelligent traffic management systems and real-time data from AGV sensors, this method becomes even more effective, allowing for adaptive route planning that balances workload and energy use dynamically across the AGV fleet. It takes into account the unique operational characteristics of AGVs such as their battery limitations, energy consumed during acceleration and deceleration, and the energy cost of sharp turns, frequent stops, and idle times. This method emphasizes generating smoother, continuous paths with fewer sharp turns and avoiding congested or high-traffic zones that lead to waiting or rerouting, which in turn wastes energy. Furthermore, by balancing the workload across multiple AGVs and optimizing traffic flow, the system prevents energy inefficiencies caused by idle waiting or route conflicts. It led to congestion, collisions, or system deadlocks in busy warehouses. Moreover, it delays order picking and reduces overall throughput, especially in high-demand environments [14].

2.3 Genetic Route Optimization Order-Picking

Genetic route optimization for order picking using AGVs is a powerful method that applies genetic algorithms to determine the most efficient picking routes within a warehouse environment. Inspired by the process of natural selection, genetic algorithms operate by evolving a population of possible picking routes over multiple generations to find a near-optimal solution [18]. It evaluates using a fitness function, typically based on criteria such as total travel distance, time, or energy consumption. Through iterative processes of selection, crossover, and mutation, the algorithm gradually refines the routes, favouring combinations that result in shorter, more efficient paths. It is particularly advantageous because it incorporates complex warehouse constraints such as aisle structures, one-way lanes, traffic rules, and vehicle-specific limitations like turning radius and payload capacity. It adapts to a wide variety of warehouse layouts and order profiles, making them suitable for both structured and dynamic environments. Moreover, it extends to optimize not just the routes but also order batching, zone assignment, and fleet coordination, enabling a holistic approach to AGV-based picking operations. It is especially useful in high-density or high-volume warehouses where manually designing routes becomes inefficient or impractical. Furthermore, improves AGV utilization, reduces energy consumption, shortens order fulfilment times, and enhances the overall efficiency of warehouse operations. However, it is computationally intensive, especially when dealing with large populations, complex fitness functions, or massive warehouses with hundreds of pick locations. It requires many generations to converge on a good solution, making them slow for real-time decision-making [15].

2.4 Genetic Algorithm Order-Picking

Genetic Algorithm (GA) order-picking for AGVs is a metaheuristic approach that applies evolutionary computation to optimize the assignment and routing of picking tasks in warehouse environments [16]. In this method, each potential solution represents a specific picking sequence or set of order assignments for AGVs, encoded as a chromosome. The GA iteratively improves these solutions through processes inspired by natural selection such as selection, crossover, and mutation aiming to minimize travel distance, reduce picking time, balance AGV workloads, or lower energy consumption. This makes GAs highly adaptable and capable of handling complex, multi-objective optimization problems often found in AGV-based order-picking systems. When used effectively, GAs optimizes not just the routing of AGVs but also the batching of orders, zone assignments, and task scheduling, making them suitable for large-scale, high-throughput warehouses. These are particularly useful in environments with dynamic order arrivals, complex warehouse layouts, and multiple constraints such as vehicle capacity, traffic rules, or time windows. However, GAs typically requires considerable computational resources and are best suited for offline or semi-real-time planning, where decisions are updated periodically rather than instantly [10].

3. Comparative Analysis

An overview of the benefits and limitations of various order picking models for the purposes of analysis is provided in this section. The different order picking models used for pick-support automated guided vehicles are examined in Table 1.

Table 1: *Comparative analysis of converters and controllers for EVs*

SL. NO	Author/Year of Publication	Methodology	Advantages	Limitations
1	Da Jiang et al [2024] [3]	A reinforcement-learning-based sampling mechanism in the prediction domain for the AGV is discussed in this paper.	It enables AGVs to learn from interaction with their environment, allowing them to adapt.	It requires more processing power and millions of samples to train effectively.
2	Hicham Kalkha et al [2024] [8]	In this paper, a significant advancement in addressing SLAP is presented for warehouse management.	It improves path efficiency and enhances task and traffic management.	However, it behaves unpredictably during early training, and its complexity to coordination strategies
3	Samnang Ou et al [2024] [10]	This paper proposes a hybrid genetic algorithm for order assignment and batching in a picking system.	It enhances the global search capability of GAs with local refinement methods.	Nevertheless, it requires powerful onboard or centralized processing units.
4	Emna Mejri et al [2022] [14]	In this paper, an EE-OPR is proposed to realize an efficient AGV.	It reduces accidents involving manual pickers or forklifts, especially in high-traffic zones.	It requires routine maintenance, battery charging, and software updates.
5	Rodrigo Furlan De Assis et al [2024] [15]	This paper analyzes the optimizing of warehouse order picking for shoe manufacturing industry applications.	Efficient and accurate picking ensures on-time delivery and correct orders.	Poorly organized or congested warehouses reduce picking efficiency.

Table 2: *Comparison of performance*

Order Picking Models	Energy Efficiency	Scalability	Optimization Quality	Compatibility
Discrete Order Picking	Variable	Low	Limited	Fair
EE - OPR	High	Medium	Good	Good
GRO - OP	High	High	Medium	Medium
GA - OP	High	High	High	High

The performance of a comparison of different order picking models is shown in Table 2. It reports the GA-OP technique achieved the best performance, and discrete order picking attained poor performance compared to other techniques.

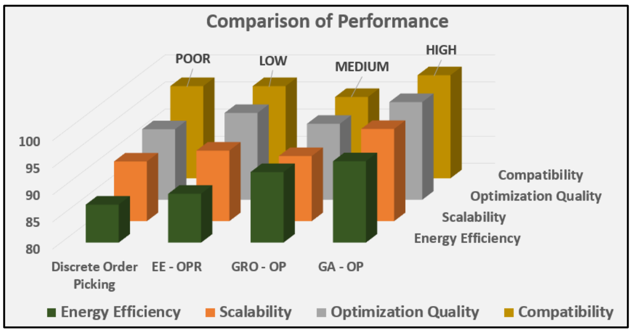

Figure 2: *Comparison of performance*

The efficiency of various order picking techniques is compared in Figure 2. The GA-OP is the best choice for high efficiency and AGV applications compared with previous techniques such as, discrete order picking is lowest performance, EE – OPR and GRO-OP are achieved medium performance of AGV applications.

4. Conclusion

The development of order-picking routing models for PS-AGVs is an essential role in enhancing the efficiency and responsiveness of modern warehouse operations. A comprehensive review of order-picking routing models is discussed in this paper for pick-support AGVs with high performance. Consequently, in this paper, four types of established order-picking routing techniques are analyzed and compared based on energy efficiency, scalability, and compatibility of AGV applications. Further, the results demonstrate the GA order-picking routing achieves the highest operational efficiency and routing. Overall, GAs offers strong adaptability and are tailored to different warehouse configurations and picking strategies, often outperforming traditional heuristic methods in terms of solution quality.

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