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ORIGINAL ARTICLE

Optimizing task allocation in multi-robot order picking systems for warehouses

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Abstract

Due to the exponential growth in demand from e-commerce businesses, warehouses are increasing in size to accommodate dynamic needs. Among the various activities in warehouses, order picking accounts for approximately 55% of the total operational costs. Mobile robots capable of lifting shelves to picking stations are employed to perform the order picking operation in these warehouses to meet rising demands. In a warehouse with multiple order-picking robots and dynamically incoming orders, assigning specific orders to each robot is a highly complex task. Optimal task allocation can enhance warehouse efficiency, thereby reducing operational costs. In the present work, a clustering algorithm is used for optimal task allocation to the order-picking robots, based on the distance between the robots, the picking station, and the shelves to be picked. Simulation experiments were conducted by varying the number of robots, as well as their positions relative to the picking station and the shelves to be picked. The evaluation covered increasingly large warehouse scenarios, ranging from 8 robots handling 16 tasks to 18 robots handling 40 tasks, enabling performance comparison of the allocation strategies under higher task–robot loads. The result indicates that the iterative K-means clustering successfully reduces task distances, enhancing overall warehouse efficiency when compared to established task allocation approaches.

1 Introduction

Warehouse automation is crucial in the e-commerce sector for swift and cost-effective order fulfillment [25]. While conveyor systems were an early solution, their lack of flexibility limits adaptability [1, 6]. Automated Storage and Retrieval Systems (ASRS) offered advantages in terms of quick accessibility but faced challenges due to expensive infrastructure [14]. In response, the Robotic Mobile Fulfillment System (RMFS) by Kiva Systems introduced shelf-carrying mobile robots, enabling a 'parts-to-picker' approach to order picking, which enhances both adaptability and efficiency compared to traditional conveyor systems and ASRS.

RMFS consists of movable shelves, shelf-carrying mobile robots, and manned picking stations [31]. The mobile robots lift shelves from storage areas and transport them to picking stations, where human pickers fulfill orders. This collaborative approach minimizes human travel within the warehouse, thereby optimizing operational efficiency [19]. However, effective coordination among RMFS resources and careful layout planning are essential for optimal performance [12, 18].

E-commerce warehouses can be classified into several types, as shown in Fig. 1a Parallel layout warehouse, (b) Vertical layout warehouse, (c) Horizontal layout warehouse, and (d) Fishbone layout warehouse. In traditional warehouses, shelves are arranged in rectangular formations with aisles and pathways in between. Recently, new warehouse layout designs have emerged, with the fishbone layout attracting the attention of warehouse designers [10, 29]. The fishbone design can improve performance by up to 20% compared to traditional layouts in single-prescribed operations and can achieve up to a 30% improvement over equivalent parallel-aisle designs, especially as the number of customer pick lists increases [5, 28].

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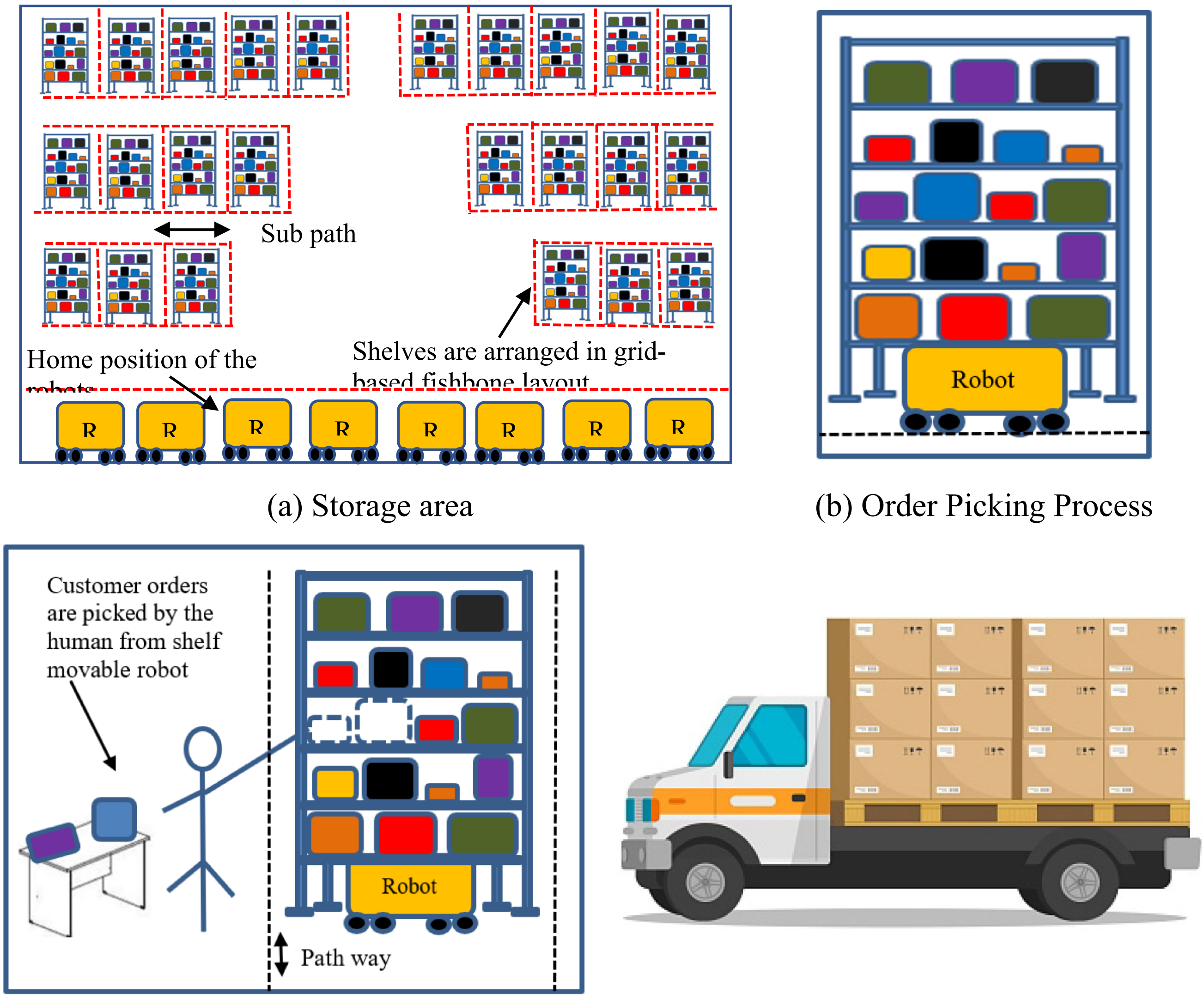


(a) Storage area

(b) Order Picking Process

(c) Consolidation area

(d) Shipping area

Fig. 2 Process in warehouse

The main activities of a warehouse consist of four processes: storage, order picking, consolidation, and shipping, as shown in Fig. 2. These activities are explained as follows: (a) Storage Area – a variety of materials are stored on shelves in the warehouse; (b) Order Picking Process (OPP) – when customers place orders, materials are retrieved from the storage area and moved to the consolidation area [15], (c) Consolidation Area – where the items for customer orders are collected from the shelves and stored with the assistance of warehouse staff; (d) Shipping Area – the customer orders from the consolidation area are delivered via the shipping process. The OPP is estimated to account for as much as 55% of the total warehouse operating expenses [9]. As customer orders increase in the warehouse, the time required for the order picking process also rises, leading to potential delays [22]. In response, companies are accepting late orders from customers and aiming to deliver products within a shorter and faster time frame [30].

OPP is initiated by customer orders, where each robot picks one shelf at a time. In this process, multiple robots are employed to move the ordered items from the storage area to the consolidation area of the warehouse. This approach, known as “Parts-to-Pickers,” is illustrated in Fig. 3. Order picking is a complex task in the warehouse due to the large volume of orders that need to be processed within a short timeframe [3]. The sequence of the stages also affects customer delivery time, as the OPP is interconnected with other stages, as described above. Multi-robot systems are particularly suitable for handling the OPP, especially as the volume of customer orders increases in the warehouse [24]. These

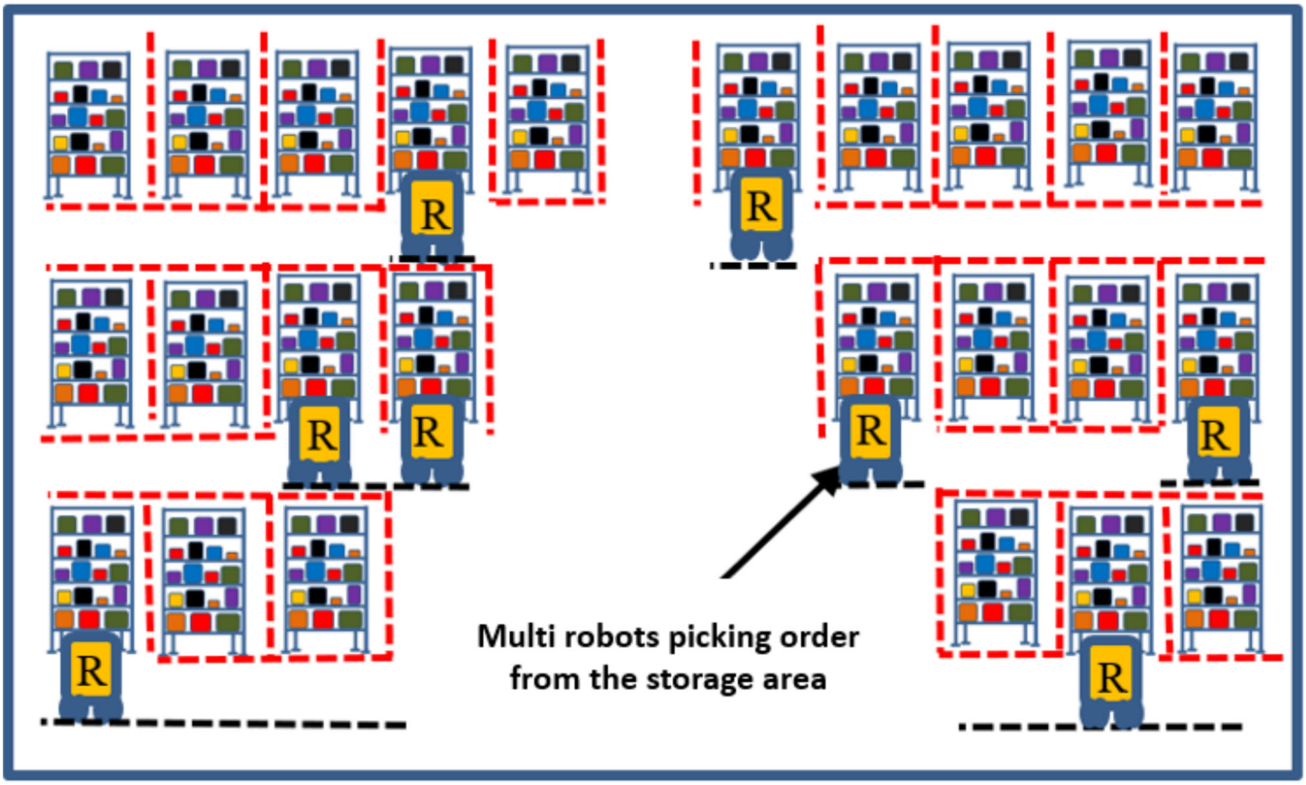


Fig. 3 Order picking process by multi robots

systems are becoming increasingly significant in industrial, commercial, and scientific applications due to their effectiveness in task allocation among multiple robots.

Autonomous mobile robots are up to 40% less expensive than Automated Guided Vehicles, as they do not require cables, magnets, lighting signals, or other costly infrastructure modifications. AMRs can complete tasks much faster and more reliably, thereby reducing both time and costs [13]. Multi-robot systems are superior to single-robot systems in handling a higher volume of orders, as the workload is distributed efficiently [17]. As a Parts-to-Pickers system, multi-robot configurations aim to overcome the drawbacks of inefficient picker travel and high personnel costs by reducing idle time. Additionally, congestion near picking stations can lead to poor warehouse performance [2]. In a multi-robot system, task allocation is crucial, as each robot is assigned to a specific customer order simultaneously, ensuring effective and timely order fulfilment.

A robot picks a shelf from the storage area and moves it to the consolidation area, where customer orders are processed by human employees. Later, the shelf is returned to its previous position in the storage area. This entire process is referred to as a "task". Typically, each task is assigned to a robot through task allocation. However, in this work, the allocation of tasks to each robot is done using the K-Means clustering algorithm [27]. Tasks are grouped into clusters or batches, and the total tasks are divided into clusters, with each cluster being assigned to a robot. This method of grouping tasks is called task allocation. Each cluster contains a number of tasks, and the allocation of tasks depends on the minimum interval between the tasks within the cluster. In each cluster (represented by a green arrow), there are 'n' number of tasks, and each task (represented by a blue arrow) consists of three subtasks (represented by red arrows), as illustrated in Fig. 4.

2 Literature survey

Task allocation is used as a solution for the Multi-Robot Dynamic Task Allocation Problem and multi-objective optimization in order to estimate and subsequently complete tasks in complex environments. Clusters synchronize their databases through task allocation, so that if a new task failure occurs in one cluster, it can replicate the database from a neighboring cluster. Each cluster follows a centralized approach to track the locations of other clusters, while the overall system operates in a decentralized manner within the work environment. Once tasks are clustered with respect to the robots, an auction takes place to assign tasks to capable robots [26]. In this study, a genetic algorithm and A* algorithm are used for task allocation and path planning for mobile robots, with an inspection carried out in an indoor

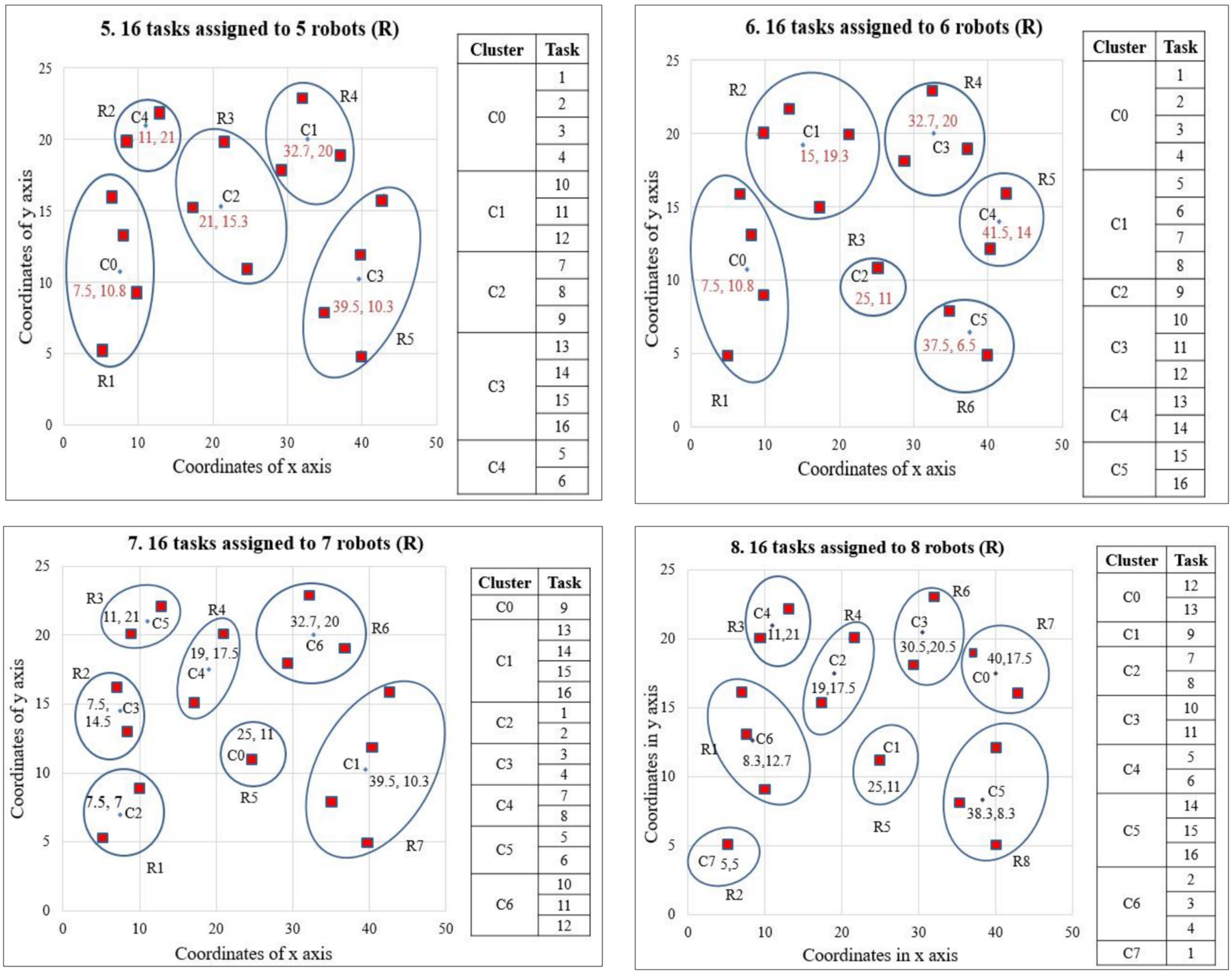


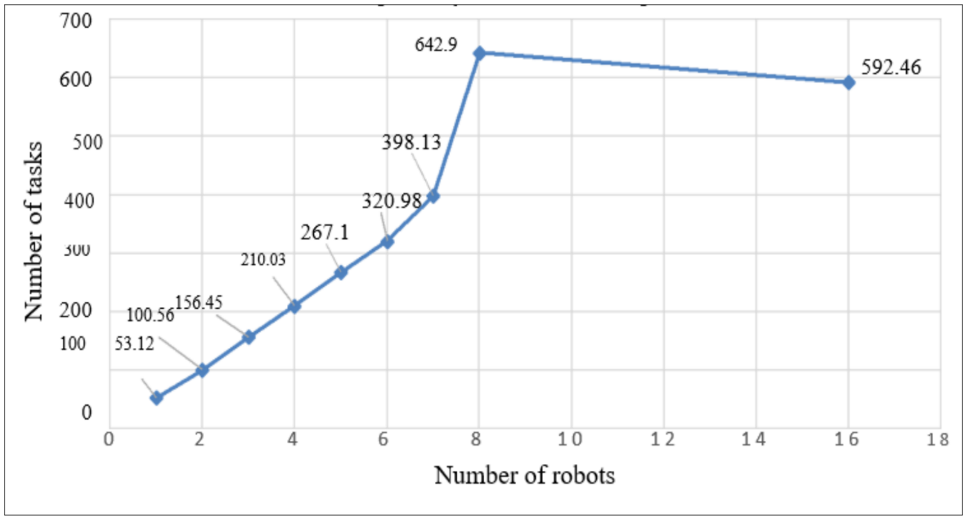
Fig. 13 Tasks assigned to 5–8 robots

equation, and task clusters are assigned based on cluster centroid calculations. Task distances are balanced across eight clusters, considering the number of robots involved.

Each cluster is allocated different tasks from the set of 16 tasks, and the task distances within each cluster are progressively reduced through multiple iterations of the K-means clustering algorithm. The tasks within each cluster are repeated over a one-hour period, enabling an estimate of the total number of tasks completed in the multi-robot system. The results demonstrate that task completion rates increase when a specific number of mobile robots are used. In this study, eight robots effectively completed repeated tasks from the set of 16 tasks, whereas 16 robots performed the same tasks with less efficiency.

The novel research on order picking tasks in a fishbone layout within warehouse environments by using K-means clustering algorithm is successfully simulated. In the present work, limited upto completion of 16 tasks by 8 robots repeatedly per hour. The simulation scope covered increasingly larger configurations, from 8 robots handling 16 tasks to as many as 18 robots handling 40 tasks, allowing assessment of how task allocation performance changes as both robot count and task volume scale. For these larger scenarios, performance metrics of the K-means clustering algorithm were benchmarked against Genetic Algorithm and Nearest Neighbour approaches to evaluate relative efficiency. Task allocation is optimized to determine the ideal number of robots for effective utilization, ultimately maximizing the task completion rate in real-time warehouse operations. Future research will extend this approach to larger-scale simulations across diverse layouts, with increased numbers of tasks and robots.

Fig. 16 Number of tasks completed by mobile robots



Authors contributions All authors contributed to the study's conception and design. Material preparation, data collection and analysis were performed by Selva Kumar Chandrasekar and S. Thirumalai Kumaran. The first draft of the manuscript was written by N. Vimal Kumar and all authors provided language help, writing assistance and proof reading of the manuscript. All authors read and approved the final manuscript.

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Data avaliability The authors confirm that the data supporting the findings of this study are available within the article.

Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval We comply with ethical standards. We provide our consent to take part.

Consent to participate The authors provide consent to participate and publication.

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