Analysing the Effects of Congestion on Hybrid Order Picking Systems using a Discrete-Event Simulator

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Abstract. In hybrid order-picking systems (OPSs), human workers collaborate alongside autonomous guided vehicles (AGVs) to pick up and transport items in a warehouse. Congestion occurs when multiple humans and AGVs operate in an area simultaneously. Congestion decreases AGV navigation performance and may cause queuing delays at packing stations. In this paper, we study the impact of congestion on the performance of hybrid OPSs. We simulate a hybrid OPS using a discrete-event simulator and evaluate the throughput under different levels of congestion and the number of AGVs. Using 10 AGVs under no congestion, we observe a throughput increase of 105% compared to a manual OPS with zero AGVs. However, this improvement decreases as the effects of congestion become stronger. Under our heaviest congestion model, there was only a 3% throughput increase for 10 AGVs. We also analyse the economic impact of adding AGVs to a hybrid OPS. Under medium congestion, the optimal number of AGVs for maximising long-term profit is 20.

1 Introduction

Global industrial trends such as digitization, globalization, and sustainability are transforming the way goods are designed, manufactured, and delivered [1]. These trends reveal new challenges for logistics management. For example, order picking systems (OPSs) handle the retrieval of goods in a warehouse to satisfy customer orders [2]. Traditionally OPSs rely on manual human labour, which covers a significant portion of the warehouse processing costs, i.e. over 50% [3,4]. However, recent advancements allow for hybrid OPSs, where autonomous guided vehicles (AGVs) work alongside humans in a shared workspace [5] (see Fig. 1). Hybrid OPSs partially automate the OPS, and can improve efficiency and scalability in small and medium-scale warehouses [6] while reducing the picker workload [7].

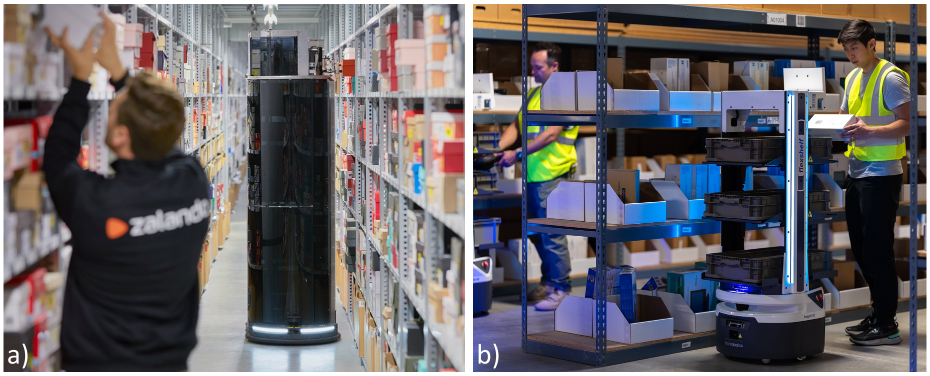
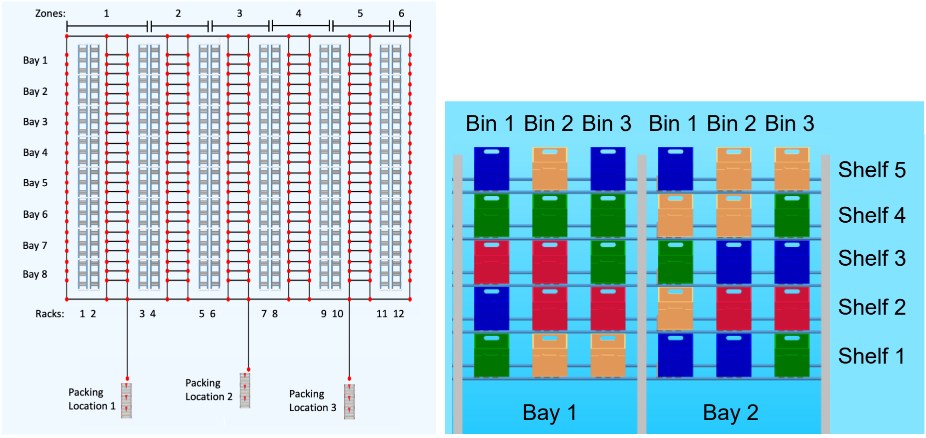


Fig. 1: Humans interacting with AGVs in a hybrid OPS. a) TORU robots by Magazino GmbH, b) Flexishelf from Zebra Technologies.

A major concern in the design and operation of hybrid OPSs is *congestion*. Congestion occurs when AGVs or humans enter the same physical space simultaneously, which forces them to slow down or stop [8]. Congestion impacts OPS efficiency [9] and in the worst case can lead to human injury or damage to the warehouse [4]. Therefore, accurate models of congestion are essential for making design decisions and estimating OPS performance. There are two main forms of congestion. *Queuing congestion* occurs when AGVs must wait for access to picking locations, drop-off locations, or charging stations [10]. *Traffic congestion* occurs when many AGVs or pickers are present in a given aisle simultaneously, slowing them down. Queuing congestion has been well studied within the context of restricted resources in warehouses, such as material handling devices [11]. However, analysis of traffic congestion has been limited to traffic engineering for highways and urban traffic [8]. Results in these domains do not translate to hybrid OPSs, where AGVs, forklifts, and humans share aisles. Moreover, traffic congestion is difficult to model in hybrid OPSs due to complex interactions between human pickers and AGVs.

Environment design and the number of AGVs are key design parameters when considering congestion. For example, if the aisles in a warehouse are sufficiently wide, traffic congestion will have little to no effect on OPS performance. In this paper, we focus on the number of AGVs, where the chance of congestion increases as multiple AGVs operate in the same physical space simultaneously. Previously, Zhang et al [8] proposed an optimization model for flow routing to alleviate the congestion. Their discrete-time interruption model links congestion and travel time by incorporating interruption events as a Poisson process. Street et al. [12] capture the effects of congestion using continuous navigation duration distributions for each congestion level. This is then incorporated into a sequential multi-robot planning framework, where AGVs compute congestion distributions that summarise the behaviour of the AGVs who planned previously.



(a) (b)

Fig. 2: (a) Top-down view of a warehouse. The connected graph with red markers represents the topological map. (b) A frontal view of a rack portion annotated with bays, bins, and shelves.

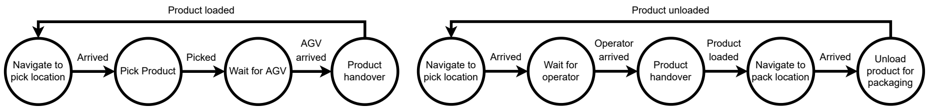
The primary contribution of this paper is an empirical study of how congestion affects the throughput and profit of a hybrid OPS. For this, we use the continuous-time discrete-event simulator (DES) CAMAS [13]. CAMAS explicitly captures the effects of congestion on navigation duration using a different duration distribution for each congestion level, similar to [12]. Unlike [8,12], we do not present an AGV routing solution to minimise congestion. Rather, we focus on how the optimal number of AGVs changes as the effects of congestion increase.

2 Order Picking Systems (OPSs)

In this section, we describe the layout of a warehouse and the operation of a hybrid OPS. For simplicity, we assume OPS orders correspond to a single product.

2.1 Warehouses

A warehouse stores products in unique locations on racks for picking. After being picked, products are sent to packing locations for packaging and marshaling. This is independent of picking and can be completed using a first-in-first-out approach by staff not in the OPS. Therefore, in this paper, we ignore packaging and marshalling, and consider orders to be completed when the corresponding product reaches a packing location. Consider Fig. 2a, which shows an example warehouse. Racks appear on either side of each aisle and are split into bays. Each bay contains a number of vertically stacked shelves, where each shelf has multiple product bins (see Fig. 2b).



(a) The human picker state machine.

(b) The AGV state machine.

Fig. 3: State machines for the AGVs and human pickers during hybrid OPS execution.

2.2 Hybrid OPS Execution

Next, we describe the execution of a hybrid OPS. An order in a hybrid OPS requires collaboration between a human picker and AGV. In Fig. 3, we present order-picking state machines for human pickers and AGVs. First, the human picker and AGV must navigate to the product location. Similar to LocusBots [14], we consider AGVs that do not follow a single picker during execution, allowing them to fulfill orders from different pickers. Upon reaching the product location, the human picks the product waits for the AGV to arrive, and then loads the product onto the AGV. After loading, the human moves on to the next order in the assigned picking schedule. The AGV then navigates to the packing location, where the product is picked from the AGV and prepared for packing. After the product drop-off, the AGV navigates to the next order location. We assume that all products are in-stock and ready for pickup at any time.

2.3 Multi-Agent Task Allocation for OPSs

To solve the order-picking problem, each order must be assigned to a picker and AGV. This corresponds to solving the multi-agent task allocation (MATA) problem [15]. In this paper, we use sequential single-item (SSI) auctioning [16] to synthesise an allocation that minimises the time to fulfill all orders, thus improving the throughput. We allocate orders to the pickers and AGVs separately, which could cause deadlocks during execution. To avoid deadlocks, we allocate orders to the pickers first and use the ordering in the picker schedules as a priority for the order during AGV allocation. With this, orders earlier in the picker schedules are serviced first by the AGVs. We also decompose the MATA problem into sub-problems by splitting the warehouse into *zones* [17]. We present an example set of zones in Fig. 2. Prior to order allocation, pickers, and AGVs can be optionally assigned to zones. Once assigned to a zone, a human or AGV can only fulfill orders in that zone, and so SSI auctions can be run for each zone independently. This constrains movement, reducing fatigue in human pickers, and battery discharge in AGVs.

3 A DES-Based Approach for OPS Evaluation

In this section, we describe how to construct a DES for evaluating hybrid OPS performance. DESs allow for rapid OPS evaluation by capturing high-level OPS behavior while avoiding the computational overhead of more realistic physics-based simulators or real-world trials [18]. In this paper, we use CAMAS [13], which captures the asynchronous continuous-time behavior of multiple agents interacting in a physical world (see Sec. 3). To accurately capture OPS behavior, CAMAS requires realistic navigation duration data from a continuous physics-based simulator or the real world (see Sec. 3.2). From CAMAS simulations we obtain statistics over OPS behavior from which we can evaluate key performance indicators (KPIs) such as throughput, total distance traveled, and AGV idle time (see Sec. 4).

3.1 Topological Maps

CAMAS abstracts a warehouse $\mathcal{W}$ into a two-dimensional topological map $\mathcal{T}$. Topological maps simplify the environment by considering the relevant locations for tasks and navigation decisions. Formally, a topological map is a tuple $\mathcal{T} = \langle V, E \rangle$ where $V \subset \mathbb{R}^2$ is a finite set of nodes representing two-dimensional locations in the environment, and $E \subseteq V \times V$ is a set of directed edges which agents can travel on. To construct a topological map for a warehouse, we place a topological node next to each stack of bins and packing location (see Fig. 2a). With this, each $\langle rack, bay, shelf, bin \rangle$ tuple maps to a single topological node from which human pickers can pick products. All shelves for a given rack, bay, and bin map to the same node, as the map is two-dimensional.

3.2 Navigation Duration Distributions

CAMAS captures picker and AGV dynamics using continuous distributions over navigation duration. For each topological edge, we require a duration distribution for each spatiotemporal situation an action may be executed under, which is referred to as the *context*. Contexts allow us to capture interactions between pickers and AGVs that affect navigation duration. One such mode of interaction is congestion, which is measured in terms of the number of pickers or AGVs present on a topological edge when a new agent begins to traverse it. Congestion increases uncertainty over navigation duration, as demonstrated in Fig. 4. To accurately capture OPS behavior, duration distributions should represent OPS execution. In [13], a phase-type distribution [19] is fit to each edge and context from empirical duration data collected from physics-based simulators or the real world. For non-navigation actions such as handovers between pickers and AGVs, or product unloading at packing stations, we collect data from an Emulate3D simulation of the hybrid OPS, which uses anthropometric models of humans [20].

3.3 OPS Execution

After specifying the topological map, duration distributions, and order allocation, we run the simulation. CAMAS simulates an OPS by sampling through a multi-robot Markov automaton which captures asynchronous OPS execution [13].

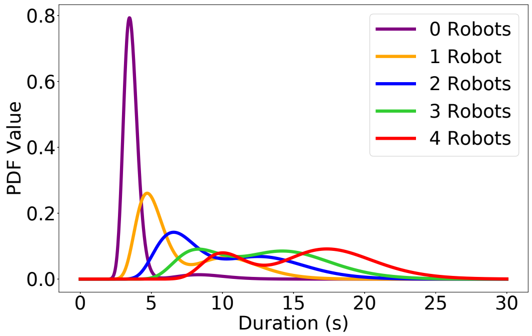


Fig. 4: Navigation duration distributions for different congestion levels on a topological edge. Reproduced from [12] with permission.

During execution, the human pickers and AGVs select actions for their allocated orders at topological nodes using the state machines in Fig. 3. When AGVs arrive at packing locations, they must queue until the packing location is free. CAMAS terminates when all orders have arrived at packing locations. CAMAS outputs a timed run of the OPS, which specifies the locations reached and actions taken by the humans and AGVs, along with the time these events occur. From this, we can evaluate the throughput by dividing the total number of orders by the time to complete all orders.

4 Empirical Study

In this section, we analyze OPS performance using CAMAS [13] under different models of congestion and numbers of AGVs. All experiments are run on Ubuntu 18.04, with an Intel Core i9-10900K CPU@3.7GHz and 32GB of RAM. All software is written in Python.

4.1 Experimental Setup

We evaluate the throughput of a hybrid OPS on the warehouse with zones in Fig. 2. There are six human pickers, one per zone, placed initially along the top row of the warehouse. We increase the number of AGVs from 10 to 70 in intervals of 10. AGVs are initially placed along the bottom row of the warehouse and are not assigned zones. As a baseline, we consider an OPS without AGVs and six human pickers, which we refer to as a *manual OPS*. Here, humans pick items and deliver them to packing locations.

To create the OPS CAMAS simulation, we use the topological map in Fig. 2 and assume the pickers and AGVs are homogeneous, i.e., the navigation delays of the human pickers and AGVs are similar. We then create five duration distributions per edge, where each distribution captures a different congestion level,

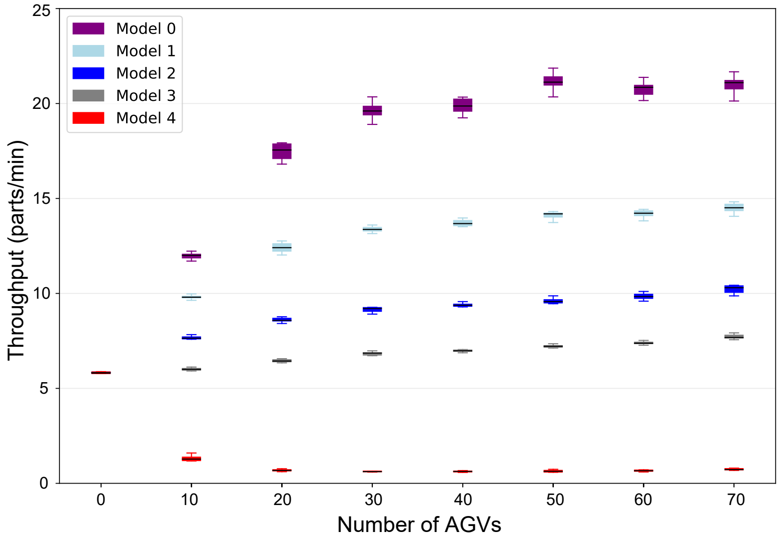


Fig. 5: Throughput results for each congestion model and number of AGVs.

i.e. number of other AGVs or pickers on an edge [12]. We consider five congestion models which capture different strengths of congestion. In model 0, all five duration distributions per edge are identical, where the distribution mean is equal to the edge length, and the variance is half the mean. This captures queuing congestion but not traffic congestion. We then extend model 0 to capture increasing traffic congestion strength. Let n denote the number of other AGVs or humans on a topological edge. Congestion models 1, 2, 3, and 4 increase the mean and standard deviation by a factor of $0.5n$, n, $1.5n$, 2^n, respectively. These increased congestion models may be representative of problems where AGVs navigate in narrow aisles, and thus have to manoeuvre around each other slowly to avoid collisions. For each congestion model and number of AGVs, we record the throughput over 10 repeats of a mission containing 600 randomly generated orders. During simulation, each order is delivered to its nearest packing location.

4.2 Throughput Results

We present the throughput results in Fig. 5 and Table 1. For congestion model 0, the throughput increases significantly as we increase the number of AGVs. By using more AGVs, we reduce the waiting duration for human pickers. However, the throughput increase begins to slow beyond 30 AGVs. This is due to increased queuing congestion at packing locations caused by the increased number of AGVs. Note that model 0 is unlikely to reflect real-world OPS execution, as traffic congestion is ignored.

Table 1 presents the percentage increase/decrease in throughput for different levels of congestion when increasing the AGVs from 0-70. The percentage

Table 1: The increase in throughput for congestion models 0-3 and 10-70 AGVs. The percentage increase is calculated with respect to the manual OPS.

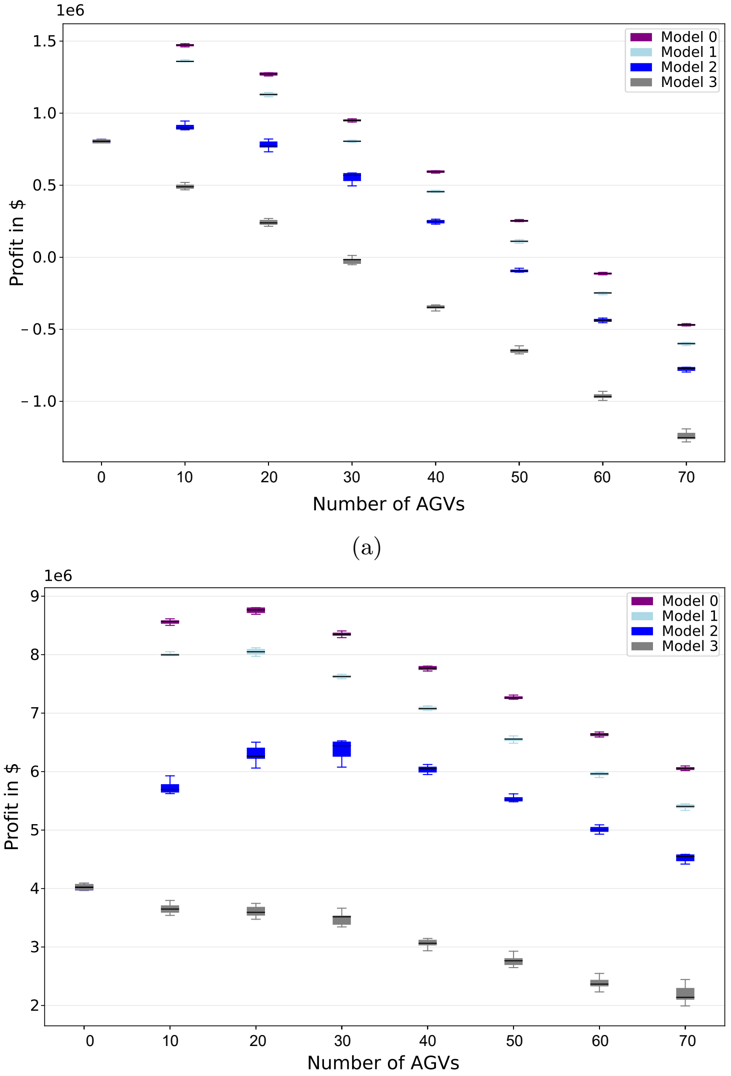
Number of AGVs	**Model 0**	**Model 1**	**Model 2**	**Model 3**
10	105%	68%	32%	3%
20	200%	113%	48%	10%
30	237%	130%	57%	17%
40	241%	135%	61%	20%
50	264%	143%	65%	24%
60	256%	144%	69%	27%
70	260%	149%	75%	32%

change is calculated with respect to the throughput of the manual OPS (approx. 6 parts/min from Fig. 5). As we begin to use stronger congestion models, the throughput decreases. This is demonstrated in Table 1, where the throughput improvement for 30 AGVs decreased from 237% to 17% between congestion models 0-3. As the congestion model increases, robots may have to wait for significant durations even under light congestion, decreasing throughput. Further, the rate of increase in throughput decreases as the congestion model increases. This is because fewer AGVs are required to cause significant navigation delays, which begins to negate the benefit of additional AGVs. For congestion model 4, the throughput decreases when any number of AGVs is added to the OPS, and so we do not include these results in Table 1. This is because the strong effects of congestion effectively block the AGVs from completing orders for long periods of time. If observed in practice, design changes would be required to the warehouse layout before AGVs could be deployed.

4.3 Profit Analysis

In this subsection, we conduct a cost analysis for the simulation results in Fig. 5. Here, we ignore congestion model 4 as the throughput decreases with the number of AGVs. Using the capital expenses for AGVs and processing costs for maintenance and labour, we analysed the profits of the OPS. For a manual OPS with six pickers and two eight-hour shifts per day, the maximum number of orders that can be fulfilled in a day is 6000. Based on current market information, we then make the following assumptions. First, the hourly wage of a human picker is estimated from the median pay for an Amazon warehouse worker, i.e. $26 per hour. Second, the average markup per item is assumed to be $1. This value will vary based on the type of items fulfilled by the warehouse. Finally, we assume the upfront cost of an AGV is $30,000, and the maintenance and operating cost per AGV is 20% of the upfront cost, i.e. $6,000 per year. The results of our cost analysis are shown in Fig. 6.

The average throughput of a manual OPS in Fig. 5 is approximately 5500 orders per 16 hour shift. With this, the average profit for a manual OPS is $0.8 million in one year and $4 million in five years (see Fig. 6a). Under congestion models 0, 1, and 2, the profit is at its 1-year maximum when deploying 10



(a)

(b)

Fig. 6: Profit estimates for hybrid OPS for four congestion models where the number of AGVs varies from 0 to 70. (a) 1-year profit estimates. (b) 5-year profit estimates.

AGVs. However, the maximum 1-year profit for congestion model 2 is similar to the manual OPS. This is because the increased congestion limits the throughput, decreasing profit. For congestion model 3, the 1-year profit is less than the manual OPS for any number of AGVs. With this, the optimal number of AGVs for maximising 1-year profit is 10 for congestion models 0, 1, and 2, and zero for congestion model 3.

Maximising throughput, the optimal number of AGVs is 30 for congestion models 0 and 1, and 20 for models 2 and 3 (see Fig. 5 and Table 1). This is inconsistent with the 1-year profit results in Fig. 6a. This is due to the high upfront cost for purchasing AGVs, which are often not recoverable within a year. Therefore, we also performed a 5-year profit analysis, as shown in Fig. 6b. Here, the profit maximising number of AGVs is 20 for congestion models 0 and 1, 30 AGVs for congestion model 2, and zero for congestion model 3, which shows no improvement for any number of AGVs compared to a manual OPS.

These results demonstrate the importance of both throughput and profit analysis to businesses in judging the number of AGVs to add to their hybrid OPS. For example, small and medium enterprises may choose fewer AGVs to maximise short-term profits for faster returns on their investment. Moreover, our results demonstrate the effects of different congestion models on profit and the optimal number of AGVs. Therefore, it is crucial that physical factors such as congestion are captured during OPS evaluation.

5 Conclusion

In this paper, we analysed the effects of congestion on the throughput and profit of a hybrid OPS using CAMAS. From 0 to 10 AGVs, the throughput increases by 105% in the absence of congestion. In more realistic congested environments, increasing the AGVs improves the concurrency in the OPS, but increases congestion. This produces a plateau in the throughput. For congestion models 1 and 2, throughput increases of 68% and 32% for 10 AGVs produced only a 35% and 11% increase in the 1-year profit respectively. Therefore, it may be preferable to analyse the long-term profit when deciding the optimal number of AGVs, where the upfront cost of the AGVs has less of an impact. Our current simulation assumes each AGV can only carry one order at a time. Therefore, in future work, we will consider AGVs with the capacity to carry multiple products. We will also analyse the distance travelled by pickers with the aim of minimising physical fatigue, and evaluate how the warehouse layout affects the throughput and profit.

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