Order picking optimization for agent-based warehouse

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***Abstract*— Simulation constitutes a crucial part of designing and operating logistics warehouses. The use of agent-based models (ABM) allows to incorporate human workers specifics in the modeling framework. Warehouse operate in a complex supply chain system and their operation should not be a bottleneck for other processes. Thus, warehouse operation must be predictable, repeatable and finally optimal. Order picking is the main process in any warehouse, being the most time consuming and therefore the most costly. This study addresses the issue of order picking process in the real scale warehouse. Optimization results are compared with the existing picking practice generated by implemented Warehouse Management System (WMS), and with common routing strategies, like S-shape or the largest gap. It is shown that evolutionary algorithm allows to improve the picking routing problem giving clear benefits.**

***Index Terms*— agent-based model; warehouse; order picking; routing optimization; evolutionary algorithm; routing strategies**

I. INTRODUCTION

This paper focuses on the human-operated picker-to-parts warehouse optimization. It is challenging task and still important despite rising popularity and increasing share of robotic and autonomous warehouses or mixed layouts [1]. Manually operated distribution centers (DC) are more frequent than automated: 80% warehouses in Western Europe are using manual operation in the picker-to-parts way [2], [3].

Agent-based models constitute strong concept, which is now underestimated in relation to the fashionable neural-based machine learning models. Both approaches, ABM approach ideally suites complex processes consisting of many simply operating components, like road traffic, evacuation systems, smart cities, and human crowds behavior. Therefore, agent framework is ideal to model human-operated DCs [4], [5]. ABM application in picker-to-parts warehouses is quite popular [6], though it must face stochastic challenges [7]. Transparency of agent-based framework is useful to get insight into internal processes and in building warehouse simulators.

However, research should not be limited to process simulations. Having a model, nothing prevents the application of optimization algorithms, which could help find optimal strategies for managing the process according a certain quality indicator and with the imposed constraints. Warehouse optimization must be driven by real operational challenges. Any methodical optimization approach should take into account the following issues [8]:

- product and order flow through the operations and supply chains;
- utilization of the facility and storage locations;
- equipment, automation, and available storage of the facility;
- product slotting, location profiles, and management of bin locations;
- auxiliary tasks like kitting, wrapping, labeling, repackaging, etc.
- compliance programs for inbound goods;
- WMS software used in the operations;
- inbound and outbound gates, and the staging space;
- organizational structure;
- benchmarks and metrics for process management.

It's all about driving down costs and gaining efficiencies to handle more throughput and better service the customer. To meet the above optimization may address improved space optimization, and labor costs, warehouse automation and proper use of in-house existing software. This work focuses on a single element of the overall approach – the picking. More efficient picking leads to higher throughput while reducing labor costs.

Above business goals can be re-translated into technical challenges that may be incorporated into the research, which as a consequence should bring improvement solutions. Thus, the academia identifies the following optimization research areas connected to the general picking task [9], [10]:

1) order picking (routing),
2) picker assignment,
3) order batching,
4) batch sequencing,
5) and location assignment.

Order picking process consist of many manual operations that consume a lot of time. The minimization of the picking travel distance is crucial for the warehouse management, as the picker's travel distance directly translates into the order picking time. This time is made up of many components, such as taking an empty carrier, planning the route, travel time to the next storage location, time to find the right product on the shelf, picking it up and placing it safely on the carrier, wrapping it with stretch film, if necessary, and "shooting off" the bar-code. Among them, travel times between locations make up at leat 50% of the total picking time. The share of other components is rather minor and is frequently neglected [11].

Next issue is the relation between the picking route

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distance and its time. There is general assumption in the literature to consider times of these component constant [12]. Moreover, once we consider the forklift speed constant as well, we result in a fact that the picking time is equivalent to the distance and time minimization is achieved by the distance optimization. Unfortunately, these times are not constant, and the forklift speed as well. Experienced pickers, perform know better the warehouse layout, have more skills and drive faster. Therefore the total difference between skillful picker and the new one, may be even fourfold. However, the batch picking process is always performed by a single picker and therefore his entire order picking time can be considered equivalent to the distanced being traveled. The picker assignment process would violate this assumption, but current research does not take it into consideration.

This work focuses on basic and fundamental warehouse picking activity, i.e. on order routing. We use global optimization evolutionary algorithm to optimize the routing path of the picker. We show that optimization helps to minimize the route lengths an as a consequence the picking time. Optimization results simulated using agent-based warehouse model are compared with real paths obtained from the WMS of real scale distribution center located in Europe. Moreover, the assessment includes two popular heuristic strategies, i.e. S-shape or the largest gap. Section II describes used algorithms and methodologies, while Section III describes the distribution center case study. Main results are described in Section IV and the paper is concluded with observations included in Section V.

II. Research areas

Considered analysis consists of two main components: the agent-based warehouse model and an optimization routine that improves order picking schedule. These two research areas are described below.

A. Agent based modeling

Applied agent model is implemented using Python language and its libraries. It consists of three main elements: agents, their interactions and an environment, in which they operate. The agents are generally human pickers in the warehouse. They perform certain atomic activities. Each one may be characterized by a different set of activities, similarly to real warehouse, where each persons has certifications for certain operations. These activities may be various, like moving (on foot or using a forklift), picking up or putting away a forklift, picking any good from the rack and placing it on the carrier, lifting and putting down the pallet, wrapping, printing and applying labels, performing up-and-down operations, and many others. The list is open and can be extended if needed.

Each basic activity are described by its execution time, which generally depends on workers skills. In our implementation this time is stochastic being generated by XGBoostLSS model [13]. Stochastic prediction gives homogeneous modeling framework of random times according to human skills profile. Moreover, it allows to capture outlying observations [14] that appear due to system errors or external reasons, pickers' tiredness or self-learning [15]. Time models are calibrated according to historical data.

Interactions between agents are relatively simple. There are no activities requiring concurrent operations. Actually, all tasks are performed by one agent and they are simply sequenced. For instance as one pallet is filled and put in the waiting place it may be picked by another agent, labeled and taken for wrapping. The scheduling of these tasks is done according to the real schedule managed by the WMS.

The picking process is implemented in a three-level hierarchical ABM structure, presented graphically in Fig. 1.

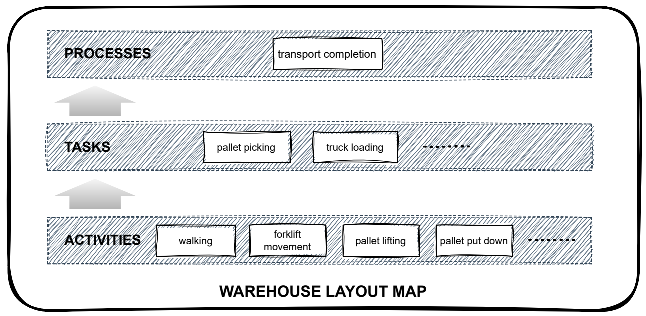


Fig. 1: ABM warehouse model structure

The functionality is described below:

– **Atomic activities** are the basic components of the model. They are conducted by a single agent (by a single person in the real warehouse). They are characterized by a specific execution time, which can be deterministic or stochastic. Parameters of these atomic activities can be set separately for each agent. Human operator walking, pallet lifting or pull down are examples of such activities.
– **Tasks** consist of conditional causal relationships between these activities. Similarly to them, tasks are performed by a single agent as well. Their realization time depends on times of component activities, so it may be deterministic or stochastic. Pallet picking, truck loading or unloading are perfect examples of tasks.
– **Processes** constitute top level model entity. They represent conditional causal relations between tasks (one or many) or atomic activities. A given process is conducted by one or many agents. Similarly to tasks, process may be deterministic or stochastic depending on the definition of utilized activities. Truck transport completion is an example of the process.

Agents operate in some designed geo-spatial environment, which is constructed according to real warehouse layout. Fig. 2 depicts such a layout of sample distribution center. In practice, the map is build using warehouse construction drawings with real dimensions.

B. Predefined heuristics

A transport task includes of a non-empty list of order records, where each order record includes particular article and the its requested number of items. The whole list is

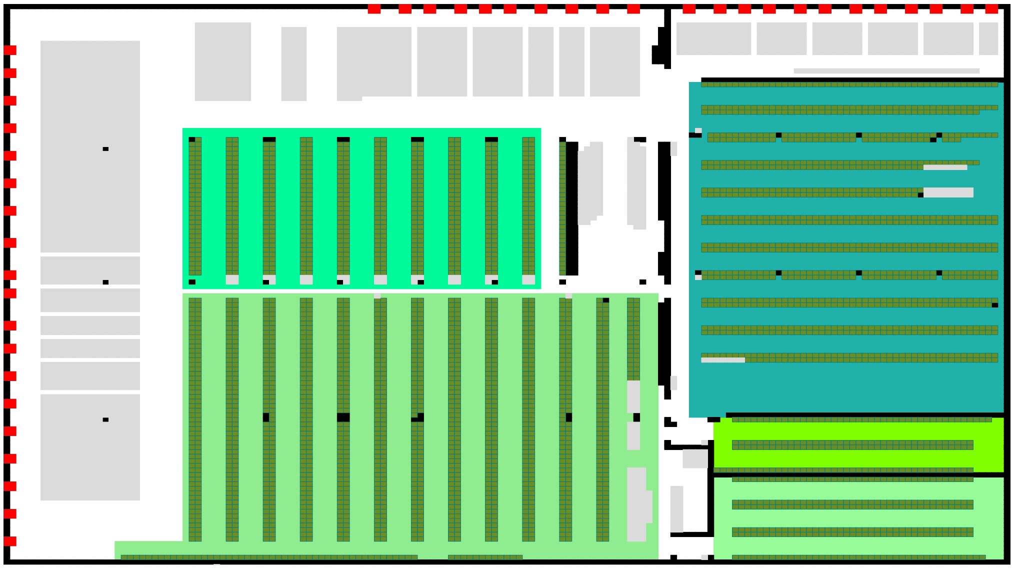
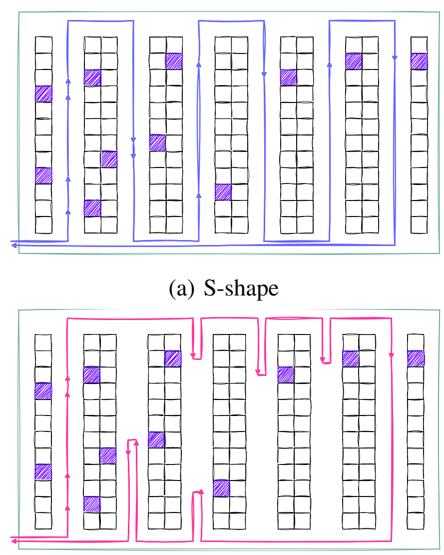


Fig. 2: Simulated warehouse layout: dark green blocks – shelf racks, light green backgrounds – sub-warehouses, gray floor – waiting areas, red rectangles – gates

frequently too large for one carrier. Therefore, it is divided into a set of batches that may be collected using single forklift in our case. Items are put into carriers, like wooden pallets or freezer containers. A forklift may carry defined number of carriers. Order list is divided into batches, and each of them includes selected order records, which should be processed together in an order defined by the WMS. The list is provided to the forklift operator using dedicated panel or voice system. It guides the order picker through the warehouse. In fact, the picking sequence is determined by a routing strategy defined in the WMS. These picking routes are simple and clear as human pickers tend to refuse routing schemes to which they are not accustomed [16].

Literature shows various heuristic strategies, like S-shape, return, mid-point, largest gap or composite [17]. In this research we compare two routing strategies: S-shape and largest gap. Comparing to an optimal strategy, they reduce congestion within aisles [2]. Fig. 3 presents graphical representation of these two strategies in a single-block warehouse, which has vertical picking racks.

The black rectangles depict item's locations to be picked during respective path. Paths following the S-shape strategy are as follows: the picker enters an aisle if at least one requested item is located in that aisle and goes through it completely. Next, he/she proceeds to the next one, which has an item. An exception may happen in the last aisle: if the picker is in front cross aisle, he/she would pick the items in the last aisle and close the path along the front aisle. The largest-gap strategy produces paths in which the picker entirely traverses both leftmost and rightmost aisles containing an item to be picked. All the other ones are entered from the back or the front ones to make the not traversed distance between two adjacent locations maximal.



(a) S-shape

(b) Largest gap

Fig. 3: Routing strategies

C. Optimization strategy

The research practice considers the problem of order batching optimization as an integer programming challenge [18]. Recent literature consist various optimization models and approaches that has been applied to the picking routing problem [15]. Generally, the batch picking problem may be considered separately, or in combination with batching, picker assignment or storage location assignment. The optimized metric typology may be distanced or time based. The task can be considered static or dynamic and deterministic or stochastic. In this research, we use static and stochastic approach that uses distance based metrics. The picking routing problem is considered as a separate activity.

Literature delivers many solutions that use various approaches [19], [20], [15], like local search with nearest neighborhood variants, custom heuristics, column generation, branch and cut, and numerous global optimization strategies: tabu search, simulated annealing, particle swarm optimization, genetic and evolutionary algorithms, and many others.

This research uses a customized evolutionary algorithm. The underlying problem closely resembles the Generalized Traveling Salesman Problem [21] and can be formulated as an optimization task aimed at arranging the shortest possible route (picking path) while visiting all the intended waypoints (products), where each waypoint may have multiple potential locations to choose from (shelves with a given product). Each solution is represented by a pair of arrays, where the first encodes the order of the waypoints, and the second determines the selection of a specific location for each waypoint.

Various genetic operators are applied to such a genome, including, among others, swapping random array elements and mixing arrays of two different solutions. Individuals are evaluated by a simple fitness function that returns values inversely proportional to the length of the encoded picking path. The algorithm utilizes a truncation selection method that has been validated in the optimization of warehouse operations [22]. The T% of the top fittest individuals are selected and reproduced in the next generation.

III. Case study description

The study is conducted using real retail distribution center located in Europe. Fig. 2 presents the warehouse layout. The storage area is equipped with single-level racks located in five zones, in which different groups of products are stored. These zones, named sub-warehouses are distinguished with different light green shades in figure. The shelf racks are marked as dark green rectangles. Gray sections represent various auxiliary storage fields, like places for empty or previously fully picked pallets, labeling or wrapping zones, or storage loading zones close to truck gates, which are denoted as red squares.

The distribution center is quite large as it handles several dozen of truck delivering goods to final customers on daily basis. A few hundreds people are employed at the warehouse ensuring its continuous operation on a 24-hour basis. More than half of them participates in the picking process, which is the focus of this study. Pickers operate forklifts that may pick up two pallets. We assume that each truck carries on maximum number of 33 pallets. We have to keep in mind that standard picking process incorporates less carriers as some space must be left for other goods that are booked in a different way. The study focuses on main picking process and other auxiliary operations, like the replenishment, wrapping, labeling or quality checks are excluded.

The warehouse pickers use four types of carriers: wooden pallets and half-pallets, freezer containers and storage blue-boxes. Each of two-pallets forklifts generally carries two pallets, four half-pallets, up to 4 containers and blue-boxes, or any available combination of them.

The goods are assigned to carriers by the existing WMS. Furthermore, this management system assigns carriers into the batches, i.e. to be handled by one forklift with human operator. Picker rides across the warehouse, collect the goods and fill carriers with assigned goods. The plan, how to ride through the warehouse, what goods should be picked and in which order is decided by the WMS and passed to the human worker using voice system or a mobile panel.

Allocation strategy of goods to individual carriers and carriers to the batches is not in focus of this paper. This work focuses on the representation of real picking process using the agent modeling framework. This ABM simulation study considers preparation of pallets for 30 truck transports. Parameters of each considered transport picking process is described in Table I. Each transports is grouped into certain number of batches and carriers. The number of visited shelves during the picking is also depicted in the table. We assume that all shelves have enough products to be picked up and product replenishment is not required. Summarizing, 489 picking routes are modeled.

TABLE I: Parameters of simulated truck transports

Id	shelves	batches	pallets	half-pallets	containers	blueboxes
1	740	14	16	1	4	1
2	923	17	17	4	3	1
3	725	14	13	4	4	1
4	851	21	18	2	7	2
5	682	12	13	2	4	1
6	718	16	21	2	4	1
7	748	15	16	3	5	1
8	775	16	19	2	5	1
9	734	16	18	5	5	1
10	738	15	18	3	5	1
11	721	14	15	3	4	1
12	764	16	21	2	6	1
13	786	14	17	4	6	1
14	769	14	15	3	5	1
15	718	14	16	1	6	1
16	772	18	11	8	5	2
17	894	20	15	4	5	3
18	751	18	13	4	8	3
19	805	16	17	5	4	1
20	735	14	15	3	4	1
21	715	19	13	4	4	2
22	742	17	13	5	6	2
23	822	13	12	4	4	1
24	826	19	14	7	7	2
25	802	22	17	6	6	2
26	895	19	18	6	8	2
27	740	19	14	6	6	2
28	796	18	14	7	6	2
29	715	15	18	3	4	1
30	754	14	18	1	5	1

We see that tasks differ and the working load is uneven. The number of visited shelves varies between 715 and 923 shelves visited, split into range of 14 to 21 batches. We see that transport tasks, assigned batches and routes vary a lot.

IV. Optimization results

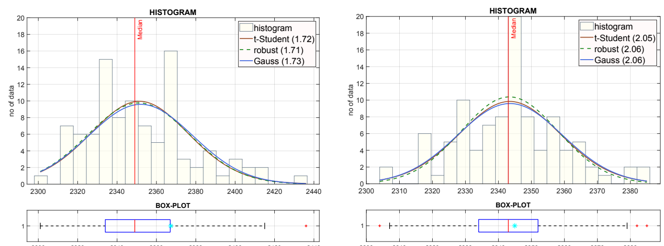
Presentation of the optimization results is split into two elements. At first, we compare optimization and heuristics results for single transportation task **#1**. In such a configuration the number of pickers in the warehouse is very

TABLE II: Statistics of single task times in seconds

	MIN	Q1	MED	Q3	MAX	R	IQR	μ	σ_G	σ_R	MAD
original	2328	2352	2364	2382	2445	117	30	2368.3	22.9	21.5	15
optimal	2280	2316	2328	2340	2367	87	24	2327.9	16.7	18.2	12
L-gap	2304	2334	2343	2351	2385	81	17	2343.5	15.9	14.7	9
S-shape	2301	2334	2349	2367	2436	135	33	2352.0	26.5	26.0	18

low, i.e. only the ones assigned to the simulated task occur during simulations. Such an idealistic simulation excludes possible conflicts between agents. Next, all tasks are subject to optimization. In this case, realistic conflicts may arise during the execution of assigned picking tasks.

The simulation model is stochastic, therefore the same simulated task may be executed with a different time. To avoid random effects, the Monte Carlo optimization setups is used. Each simulation is run 99 times and the validation is performed using resulting time quantiles and histograms.



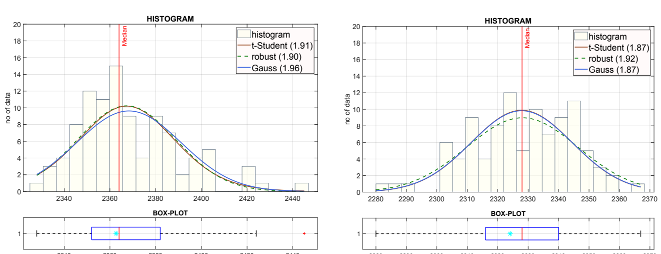
(a) S-shape

(b) Largest gap

Fig. 5: Histogram and boxplot: heuristics

A. Single task optimization

Single task optimization allows for isolated picking comparison, with excluded effects of routing conflicts. They are conducted for task **#1**. Table IIpresents comparison of statistical factors comparing obtained solutions. MIN and MAX denote minimal and maximal values, Q1 and Q3 the first and the third quantile, MED is median value. $\mathrm{R} = \mathrm{MAX} - \mathrm{MIN}$ is the data range, while $\mathrm{IQR} = \mathrm{Q3} - \mathrm{Q1}$ denotes the interquartile range. Value μ is data mean, and σ_G normal standard deviation. The σ_R denotes robust M-estimator of standard deviation evaluated using logistic function [23]. Finally, MAD denotes median absolute deviation around median, i.e. another robust scale estimator. Figs. 4 and 5 show graphically times distribution in form of the histogram and respective box-plot.



(a) Original

(b) Optimal

Fig. 4: Histogram and boxplot: optimization

We highlight some observations in the results. The S-shape heuristics results in the largest times distribution, in contrary to the largest gap approach. Optimized solution also exhibits relatively small distribution of picking times. Each heuristics diminishes resulting time. The mean value is decreased by 1.7% in the optimized version, 1.4% with the largest gap strategy and 0.7% with S-shape. The improvement in relation to median is 1.5%, 0.9% and 0.6%, respectively.

B. All tasks optimization

Similar simulation study is performed for full case. All 30 transportation task are subject to improvement and obtained picking times are compared. Fig. 6 presents histogram and boxplot for historical picking times data. We observe that picking times are highly varying due to the stochastic model of single tasks, though the histogram is quite regular with its shape similar to Gaussian.

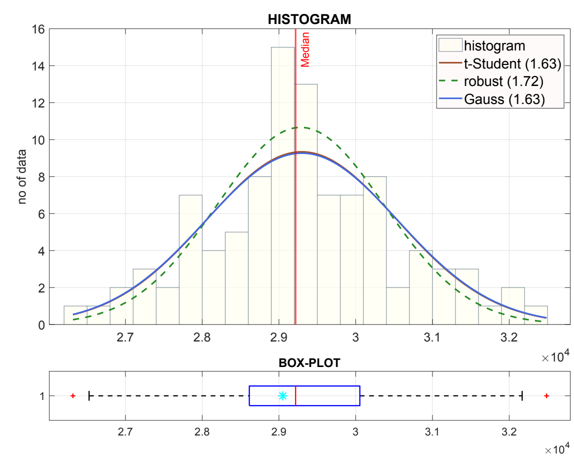


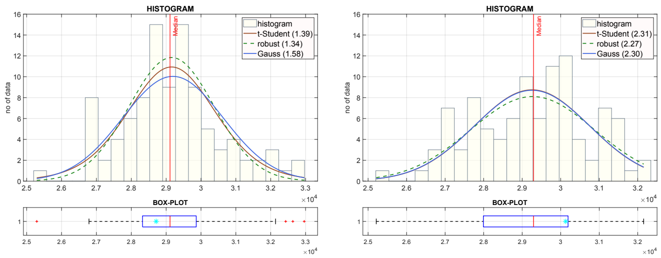
Fig. 6: Histogram and boxplot for historical data

Fig. 6 shows analogous plots for S-shape and largest gap heuristics. The largest gap variant seems to generate relatively scattered realizations, while S-shape is quite regular.

Table III presents statistical summary of the analyzed heuristics. We observe that the heuristics cannot improve the situation significantly. They increase the range of the picking times. They improve minimal times, while average times remain almost unchanged. This observations allows to conclude that the optimization has potential. Moreover, distributions of picking times require verification as they significantly impact entire simulation.

TABLE III: Statistics of all tasks times in seconds

		MIN	Q1	MED	Q3	MAX	R	IQR	μ	σ_G	σ_R	MAD
original		26316.0	28635.0	29217.0	30048.0	32487.0	6171.0	1413.0	29298.3	1252.3	1088.5	684.0
L-gap	value	25212.0	27993.0	29295.0	30187.5	32154.0	6942.0	2194.5	29255.4	1500.2	1611.1	1128.0
	change	1104.0	642.0	-78.0	-139.5	333.0	-771.0	-781.5	42.9	-247.9	-522.7	-444.0
	[%]	4.2%	2.2%	-0.3%	-0.5%	1.0%	-12.5%	-55.3%	0.1%	-19.8%	-48.0%	-64.9%
S-shape	value	25290.0	28335.0	29112.0	29862.0	32961.0	7671.0	1527.0	29194.3	1437.4	1218.4	753.0
	change	1026.0	300.0	105.0	186.0	-474.0	-1500.0	-114.0	104.0	-185.1	-130.0	-69.0
	[%]	3.9%	1.0%	0.4%	0.6%	-1.5%	-24.3%	-8.1%	0.4%	-14.8%	-11.9%	-10.1%



(a) S-shape

(b) Largest gap

Fig. 7: Histogram and boxplot: heuristics for all tasks

V. Conclusions and further research

Obtained results, though still in the initial optimization phase prove that the agent-based model of the picker-to-parts warehouse operation may be applied to optimize picking routing times. Optimization scheme is compared against two reference strategies: S-shape and the largest gap. The improvement is visible in case of a single picking task, while entire system optimization requires calibration of the auxiliary operations what should allow for consistent results.

This subject requires further research, especially in optimization hierarchical coordination between general picking tasks.

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