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Robot picker solution in order picking systems: an ergo-zoning approach

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Abstract: Manual order picking is the most labour-intensive activity in warehouses. As an alternative, robot pickers that can work alongside manual order pickers have emerged. This paper presents such a robot picker and develops a method for assigning products to two warehouse zones; one for robot pickers and one for human pickers. A Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used to develop the zoning method, minimizing human workload and maximizing the similarity of product categories in each zone. The method was verified in a case study.

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1. INTRODUCTION

Manual picker-to-parts order picking is the most labour-intensive activity in warehouses (Bartholdi and Hackman, 2017) and when performed manually it can account for up to 55 % of warehouse costs (De Koster et al., 2007). Up to 90 % of warehouses in the grocery sector apply this manual picker-to-parts order picking (Kuhn and Sternbeck, 2013). Typically, grocery warehouses decompose a large store order into several picking orders in order to deliver multiple pallets or roll cages to the store simultaneously. Orders are picked from pallets and picking often involves repetitive lifting of large and heavy items, sometimes from hard-to-reach places, causing fatigue and injuries for pickers.

In recent years, automation has reached new levels with large global actors in e-commerce, such as Amazon and Alibaba, investing heavily in the development of new automated warehouses (Boysen et al., 2019). Chui et al. (2016) categorize many warehouse operations as feasible to automate and predict that many of these jobs currently held by human operators will soon be done by technology and robots. Despite the advances in technology and automation, the barrier of entry is still high as automation involves large investments and high risk. This is particularly true for small and medium-sized warehouses that are not able to automate to the level of large centralized warehouses at this stage. As an alternative, partially automated warehouse solutions have emerged through the development and application of robot pickers for grocery warehouses (Azadeh et al., 2019). These can work side by side with human order pickers, resulting in an easily scalable solution that can be implemented with considerably less investments than the fully automated warehouse solutions.

To ensure safe and efficient picking operations in a warehouse with autonomous robots and humans working side by side, there is a need to separate picking areas into two main zones; one for robots and one for humans. The purpose of this paper is firstly to present a robot picker for picking from pallets, and secondly to develop a method for assigning products to the two warehouse zones. The model has a bi-objective function: 1) to minimize the human workload (i.e. handled weight), and 2) to maximize the similarity of product categories picked in each zone.

The paper is structured as follows. Section 2 reviews relevant literature on warehousing robotics, human-robot interaction, and ergonomics in warehousing. Section 3 presents the robot picker, and in section 4 the method for ergonomic zoning is introduced. The method is then applied to a case in Section 5, before Section 6 concludes the paper with discussions, limitations and further research.

2. LITERATURE REVIEW

2.1 Warehousing Robotics

Warehouse operations in general, and order picking in particular, are typically labour intensive processes and therefore key candidates for automation and the application of robotics (Azadeh et al., 2019). The ability to quickly process orders can provide a competitive advantage (Dubey and Veeramani, 2017, Boysen et al., 2019). However, it also leaves little room for costly errors, and these can to some degree be eliminated by automation (Mahroof, 2019, Roodbergen and Vis, 2009). There are also ergonomic advantages with automating warehouses, especially the parts that require heavy and repetitive lifting (Grosse et al., 2015, Boysen et al., 2019, Calzavara et al., 2019). The costs related to implementing an automatic warehousing system vary greatly based on the degree of automation in the selected approach (Dubey and Veeramani, 2017). At one of end of the scale are the fully automated solutions which require the largest investments and lead to full redesigns of entire supply chains (Dubey and Veeramani, 2017). At the other end, partial warehouse automation using robots provide less expensive and more flexible solutions.

Two main concepts of partial warehouse automation have emerged; parts-to-picker and picker-to-parts. Within the parts-to-picker concept, one of the approaches for using robots and humans together in warehouses most commonly discussed in literature are automated storage and retrieval systems (AS/RS)

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(Roodbergen and Vis, 2009, Gu et al., 2007, Dubey and Veeramani, 2017). This general term spans several degrees of automation and product types. Examples include advanced picking workstations where conveyor belts move items to manually operated picking stations (Boysen et al., 2019), storing consumer packages in a grid of storage bins and moving the bins to picking stations where operators fulfil orders (Swisslog, 2019), and shelf-moving robots where robots lift and move shelves to picking stations (Dubey and Veeramani, 2017). These types of parts-to-picker systems have a high degree of automation and eliminate the traveling part of the picking process, which in traditional picker-to-part warehouses account for 50 % of an order picker's time (De Koster et al., 2007). They are also able to handle small order sizes which is typical for online retail (Boysen et al., 2019). However, they also require large investments and restructuring of warehouses.

Picker-to-parts is the traditional method of order picking in warehouses (De Koster et al., 2007). However, robots can be used here as well by letting operators stay in the aisles of the warehouse and place items on arriving automated guided vehicles (AGVs). Using this method, AGVs do most of the traveling, but operators still do some of the heavy lifting. Idle times of both operators and AGVs are an issue here since waiting time can be considered as waste. There is, however, potential for even more automation in picker-to-parts systems where the robots do all parts of the picking operation by using robot arms to pick and pack the items from shelves. Although not as widespread as parts-to-picker systems, some variations exist. The TORU™ picking robot by Magazino automates the whole picking process, where the AGV automatically goes to the picking location and picks up the item without any interaction with the human picker (Azadeh et al., 2019). This is done with a vacuum gripper and boxes from a pick order are stored on the robot.

2.2 Human-Robot Interaction

The parts-to-picker and picker-to-parts concepts of automation described above are based on assigning robots and human operators separate tasks in the warehouse process. Recently, a new generation of more collaborative technologies has been introduced, including pick-support AGVs that minimize the picker travel time to fill orders (Azadeh et al., 2019). In these systems, an AGV automatically follows the operator through the warehouse while transporting the roll cages or pallets. The picker can drop off the picked items, and when the roll cage or pallet is full, the AGV returns to the depot and is replaced by a new AGV carrying an empty roll cage or pallet. Compared to the AGV-assisted picking in the picker-to-parts concept, the travel distance of operators is increased, but a lot of the issues surrounding idle times of pickers and AGVs are eliminated (Boysen et al., 2019). Human collaboration with AGVs fitted with a robotic picking arm is becoming an option with Industry 4.0 (Villani et al., 2018) and could also be an option for assisting in lifting the heaviest items in warehouses. To ensure safe and efficient picking operations in a warehouse with autonomous robots and humans working side by side, it is beneficial to separate the warehouse into two main zones; one for robots and one for humans. This allows the robots to move faster in the warehouse without as much consideration for moving forklifts and minimizing the issue of difference in speed between robots and humans which could result in queues and delays. In addition to non-robot specific benefits of employing zoning in warehouses, deciding on which products should be placed in each zone is important to minimize picking costs and balance the workloads of robots and humans (Gu et al., 2007). A relevant concept for robot-human interaction is for robots to pick the first part of the picking orders, leaving the partially stacked roll cages or pallets for the human operator in a progressive zoning system similar to what was described by De Koster et al. (2007).

2.3 Ergonomics in Warehousing

Over the last decades, the literature on order picking has had a major focus on the development of decision support models for planning the picking process in practice (for reviews, see e.g. De Koster et al., 2007, Gu et al., 2007). An area that has not received enough attention is the human factors related to order picking (Grosse et al., 2015). Physical aspects can influence performance, accuracy, and risk of injury. The most common type of injury for warehouse workers and order pickers is musculoskeletal disorders (MSDs), typically a result of the repeated lifting of heavy items in awkward body postures (Calzavara et al., 2019). One contribution in this respect is the integrated storage assignment method of Calzavara et al. (2019) for low-level picker-to-parts order picking which considers economic and ergonomic objectives. Similarly, Battini et al. (2016) applied a bi-objective method to incorporate both total order picking time and human energy expenditure.

3. GRAB™ FOR PICKING FROM PALLET

The Grab™ featured in this paper is a robot developed by Currence Robotics. It is currently under implementation in a grocery warehouse and can work in existing warehouses using the existing shelf layout. The robot uses an AGV similar to the ones described in section 2.1, but rather than having pickers in the warehouse load items on the pallet carried by the AGV, a robot arm is mounted on the AGV. The Grab™ can then move through the warehouse while picking items and stacking them on a pallet which is subsequently sent to retail stores. To pick items from the shelves, the robot arm has a vacuum gripper which can lift items up to 30 kg. The gripper has some limitations in the type of products and packaging types it can pick because it needs a flat surface to grip the items. A vision system consisting of several cameras and sensors is used to locate pallets and individual products in the warehouse and find placements for the items on the pallet on the AGV. The output from the vision system guides the arm movements of the robot. This makes the robot not too dissimilar to the TORU™ robot by Magazino (Magazino, 2019) described in section 2.1. However, there are some key differences between the two robots. The TORU™ robot is only used in pick-from-carton areas while the Grab™ can be implemented easily in a pick-from-pallet warehouse. Further, the Grab™ can pick much heavier items and larger picking orders – properties which are both critical to work efficiently in a grocery warehouse. The Grab™ can receive picking orders from the

Warehouse Management System (WMS) like manual order pickers in the current warehouse. On the picking tours, it fills a single pallet which is placed in the shipping area when completed. When creating picking lists, the WMS must consider the pickability of products and assign the unpickable products to the picking orders of the manual order pickers. The Grab™ can pick from both ground floor and second shelf (to about 3 m height, see Fig. 1), and can currently stack 1 m tall pallets (expected to increase to 2 m tall pallets within two years). The robot is not able to drive as quickly through the warehouse as order pickers on forklifts. The picking time for the prototype system in the case study is about 60 s/item (expected to be reduced to about 40 s/item in the industrialized version, within one year). This can lead to queues and congestion in the warehouse aisles, slowing down the order picking in the warehouse. Separating the warehouse into two zones with different speeds could help in solving this issue. To make up for the lack of speed, the Grab™ can work almost the entire day and at low operation costs compared to human order pickers. This results in a comparable number of items picked in one workday.

Fig. 1: Grab™ by Currence Robotics

4. ERGO-ZONING APPROACH

In order to implement the Grab™, it is necessary to separate the warehouse into two zones. The Grab™ zone will contain products which can be picked by the robot arm and typically the heavier products in order to create the bottom layers of the pallet. The second zone is a traditional manual order picking from pallet area where humans will perform the picking of smaller products in order to fill the pallet.

This section introduces a method for assigning products to the two warehouse zones, considering ergonomics and performance objective functions. Several important factors in both zoning of grocery warehouses and for the case robot have been identified, including storage assignment based on grocery store layouts and product categories, perishability of food products, human factors in order picking, robot arm gripping abilities, robot operating speed, and safety. All these factors must be considered when separating the warehouse into zones, but many are conflicting. Therefore, we use multi-objective optimization to create solutions to the problem, as discussed by Konak et al. (2006). An example of multi-objective optimization used for a similar problem is Battini et al. (2016), who optimized storage assignment based on order picking time and human energy expenditure.

Grocery warehouses are divided into three main zones based on the temperature of food products. This cannot and should not be changed to meet food quality and safety requirements (Akkerman et al., 2010). The zoning method developed here is thus used to create picking zones within these three main warehouse zones. For the development and testing of the zoning method, the dry storage area is used. This is because the case company plans to use the case robot in the dry storage area first. The products here are generally forgiving in terms of pickability and sturdiness, which makes them the most suited for testing of the robot and the robot picking - unlike for instance fruits and vegetables which would be much more difficult for the case robots to handle and thus require additional quality checks.

Two objective functions have been introduced to drive the zoning process: the total weight picked by the Grab™ (F_1) and the similarity of product categories within a zone (F_2). The decision variable x_i is a binary variable that is 1 if the item i will be allocated in the robot zone, 0 otherwise (i.e. picked by the human picker).

The first objective function is related to the ergonomics impact of the picking process, so that the higher the average weight picked by the Grab™, the better for the pickers since they will pick lower average weight (Calzavara et al., 2019). The objective function F_1 is calculated using equation 1. The numerator of the fraction calculates the sum of the weight w_i multiplied by the demand D_i of each item i in the robot zone. The denominator is simply the total demand of the robot zone. This results in an objective function where the average item weight picked by robots is maximized:

$$F_1 = \frac{\sum_i w_i \cdot D_i \cdot x_i}{\sum_i D_i \cdot x_i} \quad (1)$$

The second objective function F_2 is related to the zone assignment based on product categories: products from the same product categories are stored together in the warehouse, making it a good representation of family-grouping and in-store locations. This is useful to avoid unnecessary travel distances in the stores, providing pallets with products that are stocked in the same aisle and shelf of the store. By having similar product categories in each zone, travel distances decrease also in the warehouse because the WMS creates picking orders with products in the same area in stores, and this is represented by product category. Within the zones, the dedicated storage policy must be applied to utilize this fully. The Simpson diversity index to measure the diversity within a population categorized into groups was developed for the field of ecology (Simpson, 1949), but can also be applied to this problem where low diversity, or high similarity, is desired. It is widely used in warehousing science since it is quite simple and it does not require any additional information about the storage and retrieval system, such as layout, routing policies or picking policies.

$$S_z = \frac{\sum_{c=1}^{C} D_{cz}(D_{cz}-1)}{D_z(D_z-1)} \quad (2)$$

If the products placed in a zone is considered, a population and the product categories are used as the groupings, the Simpson diversity index can be used to calculate the similarity of product categories within a zone. Within each category, the products have different demands. Thus, the equation must be altered to include this. In equation 2, C is the total number of different categories in the dry storage area, D_{cz} is the total demand of category c in zone z, and D_z is the total demand of zone z. The equation now calculates the likelihood of two randomly selected picks done by order pickers to be from the same category. Equation 2 is used to calculate the similarity within each of the two zones. The two are then added together for calculating the total similarity of the zones in equation 3. This is used as the second objective function and should, like the first, be maximized.

$$F_2 = S_{robot-zone} + S_{picker-zone} \quad (3)$$

Evolutionary Algorithms (EAs) have been applied to solve warehouse zone assignment problems before. Specifically, Multi-Objective Evolutionary Algorithms (MOEAs) have been used to find the solutions to this bi-objectives problem. One popular MOEA variant that uses both elitism and Pareto-optimal sets is the Non-dominated Sorting Genetic Algorithm II (NSGA-II). It has previously been used in a wide variety of problem types displaying versatility, also in warehousing and distribution. Since the paper introduces the new order picking system and the zoning required for its implementation, other solving algorithms are not considered. In this paper the NSGA-II has been implemented based on the following steps. First, a bit string where each bit refers to a unique product number has been selected as the chromosome representation in the algorithm implementation. In the bit string, a one implies the product will be placed in the robot zone, while a zero implies it will be placed in the zone for human order pickers. The fast-non-dominated sorting algorithm sorts the solutions in the population based on fitness and domination. Each solution is given a rank based on which front they are assigned to by the sorting algorithm (Deb et al., 2002). Crowding-distance sorts each front in a generation based on both objective functions and calculates the total uniqueness of the solution compared to the rest of the front. Two individuals are randomly selected from the population for tournament selection. The individual with the best rank from the non-dominated sorting algorithm is returned for genetic operations. If the two solutions have the same rank, the one with the highest crowding-distance is returned. If they still cannot be separated, they are treated as equal and one of the individuals is returned at random. Two crossover points in the chromosome are selected at random. The two parent chromosomes are split at these points, mixed and recombined into two offspring chromosomes. To mutate the chromosome, strings flip mutation is selected. This is a quick and simple form of mutation where a random element in the chromosome bit string is selected and changed to the opposite value. The main output of the algorithm is a Pareto frontier containing non-dominated solutions. The solutions are different zone configurations where products are assigned to the robot and human order picker zones. To evaluate the performance of different Pareto frontiers, a similar approach to the one discussed by Lu and Anderson-Cook (2013) was selected. By approximating the area underneath the Pareto frontier, an indicator for comparing Pareto frontiers is created.

5. CASE STUDY

The ergo-zoning approach was applied to a regional warehouse which is part of a large grocery retail group. The warehouse has a floor space of 18.000 m^2. It stores and delivers approx. 6 000 SKUs to grocery retail stores, in addition to some hotels, restaurants and canteens. The warehouse uses a dedicated storage policy which matches the layouts in retail stores. Approx. 44 000 items are picked daily through the picker-to-parts concept, with an average of 60 items per picking order and an average cycle time of approx. 30 minutes. Pickers mostly work on a single picking order per tour of the warehouse.

The method was applied to the dry storage area where both ambient products and non-food products are stored, spanning 59 different product categories, with a high number of large and heavy products. Picking is currently done from full-size pallets on the ground floor. By using product information provided by the warehousing company and the assumed gripping capabilities of the robot, a map of the warehouse's dry storage area was made. Fig. 2 shows how items are distributed by product category, where each colour represents a product category, such as pasta, soda and water, seasoning, detergent, and personal care. Fig. 3 shows items pickable by the Grab™ in blue and unpickable items in red. The two figures show how there is no direct relation between product categories and pickability. For instance, the set of red dots on the top line of Fig. 3 consists mainly of cleaning products in bottles which the gripper is currently unable to grip. However, unpickable items appear in almost all areas of the warehouse.

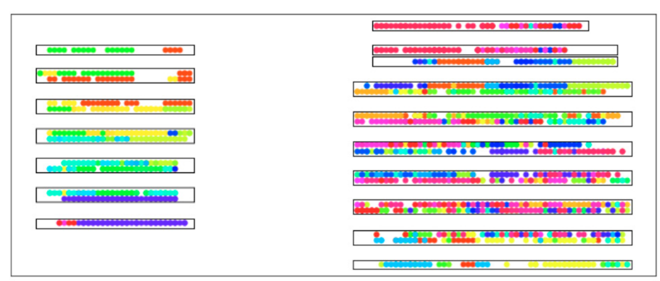

Fig. 2: Current storage location of product categories (each colour representing a product category)

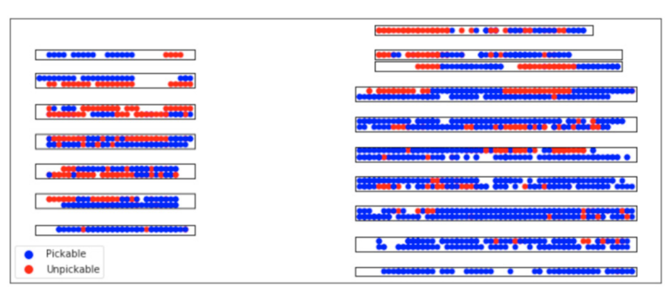

Fig. 3: Current storage location of items pickable and non-pickable by Grab™

Data from the case warehouse was used to test the algorithm, first on a small data set and then an extended application to the entire data set. The data was one month of order picking, combined with product information on packaging type and product category. The following data was used to assign products to zones. Product number: the number used to identify the product in the data. Name: the name of the product. Package: the packaging type of the product. Category: the category to which the product belongs. Weight: the weight of a single distribution pack. Demand: the number of items of the product picked in one month.

Table 1 shows how different zoning solutions affect the average weight of products lifted by robots and humans. The soda and water category has the highest demand and is often packaged in bottles which are currently not pickable by the robot. This category has an average item weight of 10,6 kg. It can be noted that for both solutions, 50 % and 70 % of demand picked by robot, the median solutions on the Pareto frontier increases the average weight of items picked by humans. The high F_1 value solutions lead to a slight decrease in average weight picked by humans. However, when the robot can pick bottles, all solutions in the Pareto frontier reduce the average weight picked by humans. The only exception is the highest category similarity and lowest average weight picked by robot, where the average weight picked by humans is unchanged.

Table 1: Objective Functions in warehouse zones

Scenarios		Robots, avg. weight (kg) (F_1)	Humans, avg. weight (kg)	Product Categories Function (F_2)
Current			5,31	
50 % picked by robot	High F_1	5,68	4,99	0,065
	Median	5,01	5,57	0,078
	High F_2	4,64	6,12	0,084
70 % picked by robot	High F_1	5,42	5,13	0,064
	Median	4,90	5,92	0,088
	High F_2	4,68	6,82	0,111
70 % picked by robot, incl. bottles	High F_1	5,74	4,50	0,068
	Median	5,53	4,90	0,071
	High F_2	5,27	5,38	0,073

The Pareto frontier of the tests including bottles is shown in Fig. 4. The curve depends on the input data of the case study, so general explanation is not achievable. However, it is worth noting that there is a difference of about 10 % for F_1 in the two extreme solutions (absolute value ~0.5, from about 5.2 to about 5.7). While in F_2 the difference is about 5 % (absolute value ~0.004, from 0.068 to 0.072). This means that moving from an optimal solution in F_1 to the optimal solution in F_2, there is an increase of 10 % in the average weight picked by humans and a reduction of just 5 % in the product categories function, with the same system performance in terms of throughput.

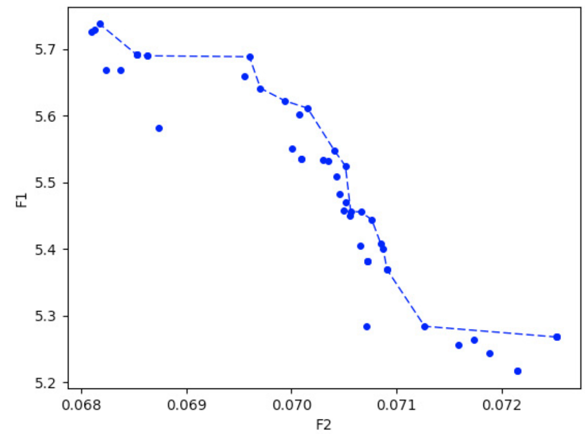

Fig. 4. Pareto frontier of tests where bottles are pickable

The results verify that the zone assignment method correctly optimizes toward the two objectives. In the solutions with high F_1, products from the same categories are placed in both zones while the average weight of items picked by robots is higher than in the other solutions. This is the expected outcome of the extreme solution of the Pareto frontier. The opposite is achieved in the other extreme solution where a large portion of the product categories is exclusively placed in the robot zone, however, the robot picks packages with the lowest average weight. Despite this, not all product categories are stored in only one zone. This can happen when the method does not explore enough of the search space and gets stuck at local optimums. Another reason why this might be a challenge is product categories with items the robot is unable to pick and heavy items. These products are often split between the zones to optimize F_1. Examples of this include the categories for soda and water products, juice products, and cleaning products, all of which contain a large portion of heavy products and are often packaged in bottles. The median solutions are also as expected somewhere in between the two extreme solutions in both F_1 and F_2. Most of the same product categories where a large percentage of the category is stored in one zone appear in both the median and high F_2 solutions. Table 1 presented the average weights picked by robots and order pickers. While the part of the goal of using robots is to decrease the workload on order pickers, the data suggests it may increase the average weight of items picked if a solution between the median and solutions with high F_2 is selected. A key reason behind the high average weight picked by humans in the results is the soda and water product category. These products are among the heaviest and the case robot is currently unable to pick bottles, which often is the packaging type of these products. For testing purposes, bottles were added to the list of robot pickable items and the average weight picked by humans was decreased for all solutions in the Pareto frontier, achieving more of the desired result.

6. DISCUSSION AND CONCLUSIONS

This paper presented a robot picker and developed a method for assigning products to two warehouse zones; one for robot pickers and one for human pickers. The case study verified that the method correctly optimizes towards both objectives – human workload and category similarity. Since the robot picker is a new solution in order picking systems, this paper is the first to introduce a method to support warehouse managers in deciding on the level of implementation of this new technology. Moreover, managers will be able to apply a more sustainable approach that considers both warehouse operations performance and order pickers' wellbeing.

The large decrease in weight lifted by human pickers in the case suggests it is important to focus future robot development on being able to pick heavy products with a large demand. Otherwise, as was the case here, the order pickers may end up with a higher workload and increased risk of injury. Robots should also be tested on a product by product level in order to accurately determine the pickability of each product.

The algorithm was tested with data from a single month. This could easily be expanded by adding more data to capture the seasonality of demand for many grocery products, enabling warehouses to pick orders in advance to balance the demand during certain periods of the year.

A limitation of the method is that it does not calculate the costs of the different solutions directly. While optimizing each of the objective functions leads to lowered costs, the trade-offs must be analyzed on a case by case basis after receiving the output from the zone assignment method. Future research should work on incorporating the costs of ergonomics and injuries caused by heavy lifting, such as MSDs, and the total grocery supply chain costs. The entire supply chain must be included since warehouses make sacrifices on performance to lower the total supply chain costs. Also, sizing of the consolidation area between the zones is ignored in the method. Future research should incorporate the different working hours of robots and humans when deciding this.

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