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Dual Robot Kit Preparation in Batch Preparation of Component Kits for Mixed Model Assembly

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Abstract: Kitting is a materials supply principle that plays a vital role for performance in mixed model assembly systems. The kit preparation process, whereby component kits are created, is central when kitting is applied. Kit preparation is a form of materials handling and is associated with several ergonomic and quality related issues. Robotics holds a great potential for decreasing the need for human labour, but literature on the topic is scarce. The purpose of this paper is to identify the time efficiency potential of a dual robot application for kit preparation. To address the purpose, a mathematical model is developed that allows dual robot kit preparation to be analysed and compared with manual kit preparation. Furthermore, the model supports identification of a suitable batch size given a lead time requirement from the assembly system. A numerical example shows dual robot kit preparation to be slightly more efficient than its manual ditto for preparation of 2, 3 and 4 kit batch sizes. The paper makes a theoretical contribution in terms of the time efficiency model of dual robot kit preparation. This model is also useful for practitioners when evaluating the potential of dual robot arm kit preparation in their own processes.

Keywords: Logistics in manufacturing, Modeling of manufacturing operations, Modeling of assembly units

1. INTRODUCTION AND FRAME OF REFERENCE

Kitting is a materials supply principle which is frequently used in mixed-model assembly. The components that are supplied to the assembly stations are arranged into kits, where each kit is a collection of different part numbers, which are all to be included in the same product (Bozer and McGinnis, 1992). Compared to the commonly used alternative of continuous supply, kitting can offer a number of benefits (Hanson and Brolin, 2013). However, a major drawback is the resource consumption required for the kit preparation, i.e. the picking and sorting of components into kits. Automation has an inherent potential to reduce the need for manual labour and thereby the running cost. In addition, kit preparation is associated with issues related to ergonomics (Hanson et al., 2018; Battini et al., 2017) and quality (Hanson and Brolin, 2013). Here too, automation may offer benefits. Robotic kit preparation has been discussed for decades (see e.g. Sellers & Nof, 1986 and Sellers & Nof 1989), but the vast majority of industrial applications are still manual. In order for robotic kit preparation to be viewed as a viable option within the industry, knowledge is needed of which performance potential it has. Such knowledge is currently missing and research on the topic is scarce.

Related to robotic kit preparation, some attention has been paid to issues of identification and grasping of randomly oriented items. Martinez et al. (2015) develop a random 3D bin picking system by integrating a vision system with a robotics system. Kootbally et al. (2018) describe components of a robot agility architecture, focusing largely on the ability to rapidly re-task kit preparation robots and how these robots can recover from errors. Mnyusiwalla et al. (2020) propose a framework for pick-and-place actions, which they apply to evaluate robotic picking systems with different grippers in a context of fruit and vegetables picking.

There are also some publications dealing with picking in collaborative solutions, where man and machine interact. Malik and Bilberg (2019) develop a methodology for the division of labour between human and robot, mainly focusing on assembly tasks but including the picking of components. Caputo et al. (2018) present a cost model for kitting that includes automated parts retrieval to a manual picking process, which is compared to fully manual processes. Boudella et al. (2018) present a model for a hybrid kit preparation system, focusing on optimising cycle time by assigning SKU:s (Stock Keeping Units) to either a robot or a human operator. With a similar focus, Fager et al. (2018) present a model for collaborative kit preparation where the picking and sorting activities are divided between a collaborative robot and an operator.

One benefit of combining a robot with a human picker is that the shared workload enables a reduced cycle time, which in turn increases the capacity of the kit preparation. Building on the research on hybrid kit preparation systems, Boudella et al.

(2018) propose that future research could address the use of two robots in the kit preparation area, instead of a robot and a human. This solution too would enable a reduced cycle time, but without the need for manual labour. However, it has not yet been addressed in the research literature. In line with this, managers who face the decision of whether to apply robotic kit preparation today lack the tools to properly evaluate this option.

The purpose of this paper is to identify the time efficiency potential of a dual robot application for kit preparation. To address the purpose, a mathematical model is developed that allows dual robot kit preparation to be analysed and compared with manual kit preparation. Furthermore, the model supports identification of a suitable batch size given a lead time requirement from the assembly system. With increasing batch sizes, the total travelling between picking locations is reduced, which can increase time efficiency (Hanson et al. 2015). At the same time, with batch preparation, components need to be sorted into the correct kits, which is an activity that is not present when kits are prepared one at a time (Fager et al. (2018). Moreover, with larger batches, the components are tied up in the batch preparation for a longer time, which means that the delivery lead time to assembly increases. The required lead time therefore constitutes a restriction to how large the kit preparation batches can be.

In section 2, the paper describes the two situations that are modelled and compared in the study. Thereafter, in section 3, the mathematical model is presented. In section 4, the model is applied, and the two situations are compared. The conclusions of the paper are presented in section 5.

2. STUDY APPROACH

In this section, an overall description is provided of the two situations modelled in the paper: manual kit preparation and dual robot kit preparation.

2.1 Manual kit preparation

Manual kit preparation processes can be designed in numerous ways. The current paper models a type of process that, based on the authors' experience and in line with empirical studies (Hanson and Medbo 2019; Fager et al., 2019; Fager et al., 2014), is commonly occurring and representative of industrial practice.

With manual kit preparation, as modelled in the paper, an operator prepares kits by walking along a material facade, picking components from shelves and sorting these into kits, see Figure 1. The workspace is an open-ended picking aisle with shelves holding SKUs on both sides. A picker walks through the aisle with a cart holding a batch of kit containers, filling the kit containers with components retrieved from the shelves. A filled kit container contains 15 different components required for an assembly object at one or several assembly work stations. The kit containers all consist of boxes and have no internal structure, why the components can be placed in any orientation within each container. The picker receives instructions from a pick-by-light system. In the shelves, there is in total 87 SKU:s stored in boxes of size 200x300x200 mm in three-level flow racks. Here, the SKU's makes up 15 component families (4-8 SKU:s per component family), which are made up by high- (50 to 80% of the volume) mid- (20 to 40% of the volume) and low-runner variants (10 to 20% of the volume).

Any of the SKU's is of a size that makes it possible to grasp one component by one hand. Furthermore, the size of some of the SKU's allows the picker to grasp multiple components at once.

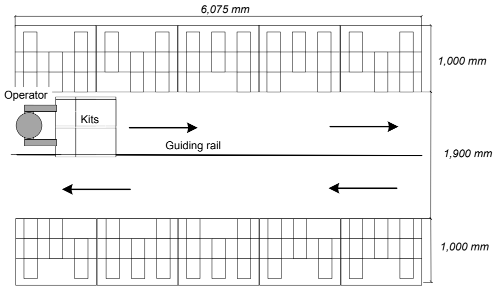

Fig. 1. Overview of manual kit preparation.

2.2 Dual robot kit preparation

With dual robot kit preparation, as modelled in the paper, two robots, separated by a conveyor belt, work together to prepare kits, see Figure 2.

One of the robots, robot 1, works inside the picking aisle, picking SKUs for a batch of kits from the shelves. It moves throughout the picking aisle on its own conveyor. When robot 1 has picked components from the shelves, it drops the components onto a conveyor belt in the centre of the aisle. The conveyor belt transports the components to the end of the aisle where the components end up in a collection zone, made up by a large bin (600x800x200 mm). At the collection zone, another robot, robot 2, picks up components and sorts them into their designated kits. Robot 1 has a 3D-camera mounted on its gripper to perform a visual analysis of the components inside each storage container before picking, in order to determine suitable gripping points. Robot 2 has a 3D-camera mounted above the collection zone, which continually analyses the contents of the collection zone. Both robots have their own tool holder located at their respective base, holding different

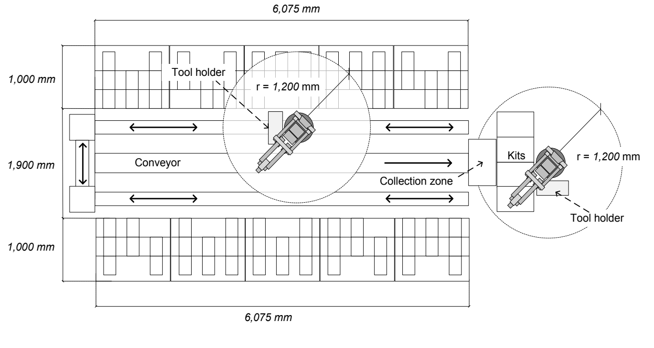

Fig. 2. Overview of dual robot kit preparation.

gripper-types. The robots change their grippers depending on the characteristics of the next component to handle.

3. MATHEMATICAL MODEL

This section presents two mathematical models, one for estimating time requirement of manual kit preparation and one for estimating time requirement of dual robot kit preparation. Both models are based on a mixed-integer linear programming approach, considering both integer and non-integer variables in the manufacturing system that the kit preparation is assumed to be part of.

The kit preparation process receives information about the kits to prepare when production orders are released. The information consists of which SKUs are needed, the quantities, and which manufacturing order each kit is needed for, presented as a pick list. Each pick list presents information about the kits in the batch of batch size B and contains N_i order lines. Each order line i holds information about the part number associated with the SKU, the quantity q_{SKU} to pick, the storage location at the workspace whereat, and the quantity q_{kit} each kit j should receive.

In the following, the models for manual and dual robot-arm kit preparation are presented. The terminology used is in accordance with Wentzky et al. (2019) and terms used in previous works on the topic (e.g. Boudella et al. 2018).

3.1 Modelling manual kit preparation

In manual kit preparation, the operator's time requirement consists of picking and sorting components, travelling, as well as administration of picking information. Manual kit preparation has been modelled before by e.g. Fager et al. (2019) and Boudella et al. (2018). The approach in this paper is based on these previous works.

The cycle time, $T_{CT(M)}$, is the time required by an operator for completing a batch of orders, T_{OP}.

$$T_{CT(M)} = T_{OP} \tag{1}$$

Time requirement of manual order picking activities is can be composed of travelling time $T_{travel(OP)}$, picking time $T_{get(OP)}$, and sorting time $T_{place(OP)}$ (Fager, 2018).

$$T_{OP} = T_{get(OP)} + T_{place(OP)} + T_{travel(OP)} \tag{2}$$

The pick task $T_{get(OP)}$ involves that the picker receives and interprets information $t_{I(SKU)}$, searches $t_{S(SKU)}$, grasps components $t_{G(SKU)}$, and performs pick-from confirmations $t_{C(SKU)}$. Here, $t_{I(SKU)}$, $t_{S(SKU)}$, and $t_{C(SKU)}$ is performed once for every order line N_i. With grasping, to grasp one component requires time $t_{G(1)}$, but grasping more than one component takes $t_{G(>1)}$ for every extra component. Furthermore, $t_{G(SKU)}$ is affected by pickability, which refers to the extent by which components adheres to other components, or the container walls. This is common with, for example, springs. Furthermore, pickability also applies for components that are difficult to grasp, as these would require more time to be properly grasped (Hanson and Medbo, 2019). In this paper, pickability is represented by ρ. Normal pickability is $\rho = 1$ and means that components can be grasped in a straightforward manner. Low pickability is $p = 0$ and means that components a problematic to grasp swiftly and require more time to grasp properly. An individual analysis of each SKU must be performed to determine its pickability ρ^i. For components with low pickability, a time addition of α has to be accounted for.

$$T_{get(OP)} = \sum_{i=1}^{N} \left(t_{G(1)} + t_{G(>1)} \cdot (q^i_{SKU} - 1) + \alpha \cdot (1 - \rho^i) + t_{I(SKU)} + t_{S(SKU)} + t_{C(SKU)}\right) \tag{3}$$

The second term in (2), T^{OP}_{place}, accounts for the time spent by the picker on the sort task. Here, time is needed for the picker to receive and interpret information, $t_{I(kit)}$, searching and identifying the correct kit container $t_{S(kit)}$, placing components $t_{P(kit)}$, and performing place-to confirmations $t_{C(kit)}$. With the sort task, the terms $t_{I(kit)}$ and $t_{S(kit)}$ occurs once for every order line N_i, but placing components $t_{P(kit)}$ in kits and performing place-to confirmations $t_{C(kit)}$ occurs for every component. Additionally, with placing components, the picker spends more time on placing a single component than on placing additional components after placing the first one, as the picker is already at kit carrier after placing the first component. Therefore, $t_{P(1)} > t_{P(>1)}$.

$$T_{place(OP)} = \sum_{i=1}^{N_i} \left(t_{P(1)} + t_{P(>1)} \cdot (q^i_{SKU} - 1) + t_{C(kit)} \cdot q^i_{SKU} + t_{I(kit)} + t_{S(kit)}\right) \tag{4}$$

Travel time in (2), $T_{travel(OP)}$, is calculated from the travelling speed and total travel distance. In the considered case, the total travelling distance is calculated from the number of shelf-sections N_s and the length of each shelf-section $\sum l_{shelf}$, as the picker passes by all shelf-sections during a picking tour. The picker has the average speed v_{OP}. As with manual order picking in warehouses, some tasks can be performed while travelling, for example administration (Battini et al., 2015). Therefore, the proportion μ_{travel} of the travelling time is here considered to occur in parallel with the tasks $t_{I(SKU)}$ and $t_{S(SKU)}$, for the first order line in each shelf. Also for each shelf section, the picker must start t_s and park t_p the trolley.

$$T^{OP}_{travel} = \sum_{s=1}^{N_s} \left(\frac{l^s_{shelf}}{v_{OP}} + t_s + t_p - \mu_{travel} \cdot \left(t_{I(SKU)} + t_{S(SKU)}\right) \right) \tag{5}$$

The cycle time of manual kit preparation can now be estimated from (1) with (2), (3), (4), and (5).

3.2 Modelling dual robot kit preparation

Various applications for robot-supported kit preparation have been modelled before (see e.g. Fager et al., 2019; Boudella et al., 2018; Coelho et al., 2017). Although, as noted in the introduction, no study has previously considered the use of two robot arms that together carry out kit preparation. The model of robotic kit preparation presented here builds on the available literature, and makes use of a standardised vocabulary in accordance with Wentzky et al. (2019).

With robotic kit preparation, the cycle time $T_{CT(R)}$ consists of the time required for robot 1, T_{R1}, to pick SKUs, the time required for transporting components on the conveyor belt T_{CV}, and the time required for robot 2, T_{R2}, to sort components into kits. The cycle time can be estimated as:

$$T_{CT(R)} = T_{R1}^{i=1} + \sum_{i=2}^{N_i-1} T_{CT}^{i} + T_{R2}^{i=N} \tag{5}$$

Here, special situations occur at the first order line ($i = 1$) and the last order line ($i = N_i$) since robot 2 has no components to sort before order line $i = 1$, why $T_{CT(R)}^{i=1} = T_{R1}^{i=1}$. Similarly, robot 1 has no SKUs left to pick at the last order line $i = N_i$ and $T_{CT(R)}^{i=N_i} = T_{R2}^{i=N_i}$. For all order lines in between 1 and N_i ($1 < i < N_i$), the cycle time is estimated based on the which one of robot 1 and robot 2, and the associated conveyor belt transport, that takes the longest time for completing the work, represented in the term $T_{CT(R)}^{i}$, where robot 1 always works ahead of robot 2. Hence:

$$T_{CT(R)}^{i} = \max\left(T_{R1}^{i+1} + T_{CV}^{i+1}, T_{R2}^{i} + T_{CV}^{i}\right) \tag{6}$$

For robot 1, its time expenditure consists of the time for moving along its translational axis to the correct locations relative the shelves, which requires the time T_{move}, the time for the vision system to identify components to pick, T_{vision}, the time for grip a component T_{get}, the time required for placing component T_{place}, and the time required for tool change T_{tool}.

$$T_{R1} = T_{tool(R1)} + T_{vision(R1)} + T_{move(R1)} + T_{get(R1)} + T_{place(R1)} \tag{7}$$

$$T_{R2} = T_{tool(R2)} + T_{vision(R2)} + T_{move(R2)} + T_{get(R2)} + T_{place(R2)} \tag{8}$$

To support tool changes, both robot 1 and robot 2 have a tool holder at their base, and a tool change requires the time $t_{tc(R1)}$ for robot 1 and $t_{tc(R2)}$ for robot 2. A tool change is only required if two consecutive order lines cannot be handled by the same tool, in which case the tool change index $\tau^i = 1$. If no tool change is required, $\tau^i = 0$. Hence:

$$T_{tool(R1)}^{i} = \left(1 - \tau_{R1}^{i}\right) \cdot t_{tc(R1)} \tag{9}$$

$$T_{tool(R2)}^{i} = \left(1 - \tau_{R2}^{i}\right) \cdot t_{tc(R2)} \tag{10}$$

The time for robot 1's vision system to analyse components, T_{vision}, starts when robot has positioned its gripper and camera above the bin from which to pick components, and ends when then the robot starts the get activity. On average, it requires the time $t_{vis(R1)}$, but the analysis time has some variability depending on how well organised the components in each bin are, represented by σ. Hence:

$$T_{vision(R1)}^{i} = (1 + \sigma_{R1}^{i}) \cdot t_{vis(R1)} \tag{11}$$

With robot 2, there is vision system camera positioned over the collection zone that continually observes what components are in the collection zone. Thereby, robot 2 never has to wait for the vision system analysis to complete. Accordingly:

$$T_{vision(R2)}^{i} = 0 \tag{12}$$

For robot 1, T_{move} consists of moving from a location within the aisle corresponding to the SKU associated with order line i, to a location corresponding to the SKU associated with order line $i + 1$. The time required for moving is determined from the distance travelled $\Delta^i = |L_{SKU}^{i} - L_{SKU}^{i-1}|$ and the linear movement speed $v_{lin(R1)}$, according to:

$$T_{move(R1)}^{i} = \Delta^{i} \cdot v_{lin(R1)} \tag{13}$$

With robot 2, it remains in position in front of the kit containers, hence the move time is always zero.

$$T_{move(R2)}^{i} = 0 \tag{14}$$

With gripping time, T_{get}, there is a risk for both robot 1 and robot 2 that they fail to grip a component on their first try, ε_{R1} and ε_{R2}, whereby the get activity must be reattempted. The time for manoeuvring into position and gripping a component, then returning, for robot 1 consists of the distance to the shelf level h, d_{SKU}^{h}, whereat SKU i is stored at and the positioning speed $v_{pos(R1)}$. is $t_{get(R1)}$ and $t_{get(R2)}$, which depends on what gripper k is used. For each component, k has to be determined. Furthermore, robot 1 must turn from the conveyor towards the shelves before starting the get activity, represented by $t_{turn(R1)}$. Accordingly:

$$T_{get(R1)}^{i} = \left(1 + \varepsilon_{R1}^{k^i}\right) \cdot t_{grip(R1)}^{k^i} + \frac{2 \cdot d_{SKU}^{h^i}}{v_{pos(R1)}} + t_{turn(R1)} \tag{15}$$

For robot 2, the components arrive at the collection zone one by one and the gripping activity is simpler than for robot 1. Accordingly:

$$T_{get(R2)}^{i} = (1 + \varepsilon_{R2}^{k^i}) \cdot t_{get(R2)}^{k^i} \tag{16}$$

The time required for placing components, T_{place}, depends on what gripper k is used, and is represented by t_{place}. Furthermore, robot 1 must turn towards the conveyor before components can be placed there, $t_{turn(R1)}$. Robot 2 must change its position from the collection zone to kit container j, distance d_{kit}^{j}, to place a component while moving at its positioning speed $v_{pos(R2)}$, and then return to the collection zone. Hence:

$$T_{place(R1)}^{i} = t_{place(R1)}^{k^i} + t_{turn(R1)} \tag{17}$$

$$T_{place(R2)}^{i} = \sum_{j=1}^{B} \left(\frac{2 \cdot d_{kit}^{j} \cdot q_{kit}^{ij}}{v_{pos(R2)}} + t_{place(R2)} \right) \tag{18}$$

The time required for the conveyor to transport components to the collection zone, T_{CV} is given by the current location within the aisle of robot 1, L_{SKU}^{i}, and the conveyor's speed v_{CV}. Accordingly:

$$T_{CV}^{i} = v_{CV} \cdot \sum_{i=1}^{N} L_{SKU}^{i} \tag{19}$$

Now, the time requirement for robot 1 can be estimated from (7) with (9), (11), (13), (15), and (17). The time requirement for robot 2 can be estimated with (8) with (10), (12), (14), (16), and (18). The time requirement of the conveyor is estimated from (19). The cycle time of robotic kit preparation can, then, be estimated with (5) and (6).

4. MODEL APPLICATION AND COMPARISON

This section presents an analysis of robotic kit preparation and a comparison with manual kit preparation from an efficiency standpoint. The case example is based on the systems described in section 2. All results presented in the section are based on preparation of 500 kits, which roughly corresponds to a daily production volume at large scale manufacturer. The kit contents, in terms of which components the kits were composed of, were created from assuming that each component family was composed of high- and low-runner component variants, as was described in section 2. The objective of the example is to determine which batch size that allows a lead time requirement of 8 seconds per kitted component to be fulfilled, which roughly corresponds with a typical lead time window in industry.

The notations used and example values are shown in **Table 1**. The example values have been identified from previous publications about manual kit preparation (e.g. Hanson and Medbo, 2019; Battini et al., 2015), robot-supported kit preparation (e.g. Boudella et al., 2018; Fager et al., 2019), and from small-scale tests with robot picking in a laboratory setting.

Table 1. *Example values used.*

Notation	Description	Value(s)
α	Time (s) for picking with low pickability	0.58
B	Batch size	1-4
Δ	Linear move distance (m) between order lines $i-1$ and i (robot 1)	0-7
d_{kit}^{j}	Linear distance (m) for placing components into kit j (robot 2)	[1.2,1,1,1.2]
d_{SKU}^{h}	Linear distance (s) for positioning at shelf level h (robot 1)	[1.1,0.9,1.2]
ε_{R1}^{k}	Grip failure rate with gripper k (robot 1)	[0.15,0.25,0.35]
ε_{R2}^{k}	Grip failure rate with gripper k (robot 2)	[0.1, 0.2, 0.3]
h	Shelf level index	1-3
i	Order line index	1-34
j	Kit container index	1-4
k	Gripper index	1-3
l_{shelf}^{s}	Length (m) of shelf s	1.2
N_i	Number of order lines in a work cycle	27-34
N_s	Number of shelves at workspace	10
σ_{R1}	Variability of vision analysis time (robot 1)	0-0.2
ρ	Pickability index, 1 (normal pickability) or 0 (low pickability) (operator)	0-1
q_{kit}	Quantity to sort into kit j	1-4
q_{SKU}	Quantity to pick from shelves at order line i	1-4
$T_{vision,R2}$	Time (s) for vision analysis (robot 2)	0
$T_{move(R2)}$	Time (s) for moving (robot 2)	0
$t_{vis(R1)}$	Time (s) for vision analysis before get activity (robot 1)	2
$t_{get(R1)}^{k}$	Time (s) for picking with gripper k (robot 1)	[1.3, 1.7, 1.1]
$t_{get(R2)}^{k}$	Time (s) for picking with gripper k (robot 2)	[1.1, 1.5, 0.9]
$t_{tc(R1)}$	Time (s) for switching gripper (robot 1)	1
$t_{tc(R2)}$	Time (s) for switching gripper (robot 2)	1
$t_{turn(R1)}$	Time (s) for turning 180° to access shelves or conveyor (robot 1)	1
$t_{C(SKU)}$	Time (s) for performing a button-press (picker)	1.01
$t_{I(kit)}$	Time (s) for identifying a lit up light indicator (picker)	0
$t_{S(kit)}$	Time (s) to search and identify the correct kit container (picker)	0.75
$t_{P(1)}$	Time (s) required to place the first component in a kit	0.66
$t_{P(>1)}$	Time (s) required to place additional components in a kit	0.57
$t_{C(kit)}$	Time (s) for pressing a button associated with a kit-container	0.87
t_s	Time (s) to begin moving with the cart	0.2
t_p	Time (s) to stop moving with the cart	0.2
$t_{I(SKU)}$	Time (s) for receiving information about what to pick by help of light indicators	0
$t_{S(SKU)}$	Time (s) to search for and identify a light indicator	1.37
$t_{G(1)}$	Time (s) to grasp one component	1.12
$t_{G(>1)}$	Time (s) to grasp additional components	0.52
τ_{R1}	Indicates if a tool switch is needed for handling next SKU, 0 if needed (robot 1)	[0,1]
τ_{R2}	Indicates if a tool switch is needed for handling next SKU, 0 if needed (robot 2)	[0,1]
μ_{trav}	Fraction of travelling performed during other activities	0.1
$v_{lin(R1)}$	Linear move speed (m/s) of robot 1	1
$v_{pos(R1)}$	Positioning speed (m/s) of robot 1	1
$v_{pos(R2)}$	Positioning speed (m/s) of robot 2	1
v_{CV}	Conveyor speed (m/s)	0.5
v_{OP}	Travelling speed (m/s) of the operator	1

In kit preparation, the batch size affects the number of components that can be picked at once of an SKU and, consequently, the average travel distance per kitted component. The effect of various batch sizes on the efficiency of robotic kit preparation relative to the lead time requirement is shown in Figure 3.

The result in Figure 3 shows that both manual and robotic kit preparation fulfil the requirement of the lead time of 8 seconds at a 4-kit batch size. Robotic kit preparation shows a slightly

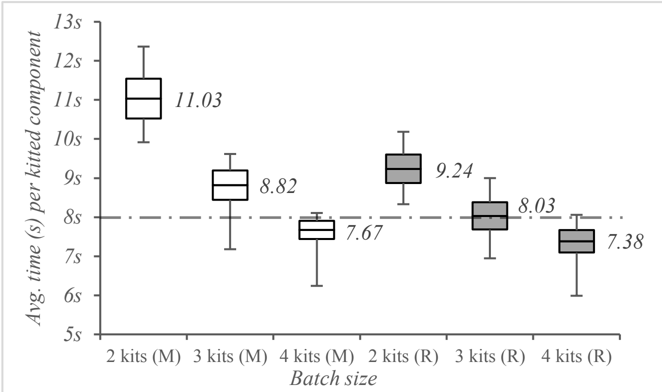

Fig. 1. Time efficiency associated with batch size for manual (M) and robotic (R) kit preparation. The horizontal line indicates the lead time requirement (8 seconds per kitted component) in the example.

higher efficiency over manual kit preparation for all considered batch sizes with biggest differences for 2 kits. The increased cognitive complexity in manual kit preparation when introducing more kits should also be considered as a parameter. Cognitive support will be vital for the operator as the batch size increases.

5. CONCLUSIONS

As showed in the model application, there is an efficiency potential for dual robot kit preparation over its manual ditto. With a growing market of flexible robots, applications such as the one considered in the paper are likely to become more frequent in industry. Aside from efficiency, there could also be differences in, for example, quality and ergonomics if the batch sizes increase, as the operator's task becomes more cognitively complex.

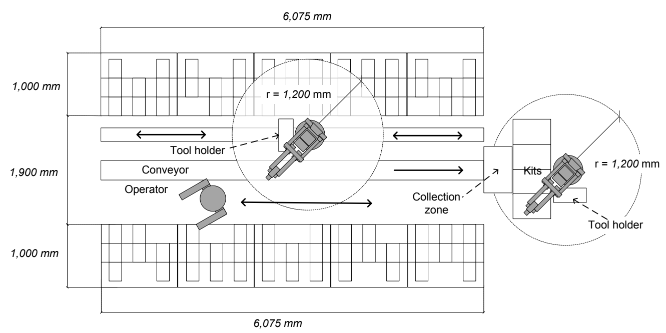

Figure 4. Future application with human-robot collaboration.

Although manual and dual robot kit preparation were considered separately and compared in the paper, a combination of the two setups is also conceivable, as illustrated in Figure 4. This combination could be achieved by use of a role-based planning approach between the operator and the robot (Weichhart et al., 2018; Makino and Arai, 1994). A benefit of such a collaborative approach could be a higher resource flexibility, as well as an overall increase in efficiency owing to that the operator and robots work in parallel. To design a system that contains a mix between collaborative robot applications and operators, as illustrated in Figure 4, safety guarding solutions and risk assessments analysis is necessary. Future research should explore collaborative variations that involve operators of the setup that was considered in the paper.

Technology continues to evolve, presenting new solutions with respect to robots for collaborative applications, IoT-platforms for communication, scheduling and control, and cognitive automation. Research plays and important role in this future, and important factors such as organization and competence need to be considered alongside technological advancements.

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