

Kit Preparation with Cobot-supported Sorting in Mixed Model Assembly

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Abstract: Kitting is a common approach of materials supply with mixed-model assembly, by which components are supplied to the assembly process in pre-sorted kits. With kitting, the kit preparation is a labour intensive process and order batching is often applied to enhance efficiency. Here, improved quality and efficiency by means of automation is desirable, but knowledge of the potential of collaborative robots to support kit preparation with order batching is lacking. The purpose of this paper is to identify the potential of cobots to support time-efficient kit preparation with order batching, when the pick task is performed manually and a cobot carries out the sort task. A modelling approach is applied with experimental data from laboratory experiments to compare the cycle time between fully manual and cobot-supported kit preparation with order batching. The findings suggest that a cobot-supported sort task leads to a comparable average cycle time, with less variability of the cycle time, when compared to the fully manual setup. The paper contributes several insights on the application of cobots to support kit preparation, and the model developed in the paper can be used by practitioners to assess the potential of cobots to support their processes for kit preparation.

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1. INTRODUCTION AND STATE OF THE ART

In mixed-model assembly, there is usually a multitude of component variants and the materials supply to the assembly processes is essential. Here, kitting – meaning to supply assembly with components pre-sorted in kits for each assembly object – is commonly used and has been associated with many benefits (Medbo, 2003). With kitting, the kit preparation process is normally performed manually, and *order batching* – meaning that several kits are prepared during the same work cycle – is often applied to enhance the time-efficiency and promote a low running cost (Hanson and Medbo, 2016). With order batching, the operator must, in addition to the *pick task* of retrieving the correct SKUs from the shelves, also perform a *sort task*, by which the picked components are sorted into the kits during the work cycle. The sort task can be complex when there are many kits in the batch, and may compromise the kit quality due to the risk of placing components in the wrong kit (Fager, 2018). Previous studies have shown that robotics can support both quality and efficiency of the pick task in kit preparation (Boudella et al., 2018), but approaches for supporting the sort task by means of robotics has so far received less attention. Studies on assembly

operations have shown that with the emergence of safe, lightweight and flexible robots, applications that allow for human-robot collaboration are viable (Sadrfaridpour and Wang, 2018). The prospect of human-robot collaboration in applications of kit preparation is desirable, especially with respect to the sort task. So far, relatively little attention has been paid to how applications of collaborative robots – so called *cobots* – can support kit preparation, and more knowledge is needed both in the literature and in industry to understand the potential. The purpose of this paper is to identify the potential of cobots to support time-efficient kit preparation with order batching, when the pick task is performed manually and a cobot carries out the sort task. A modelling approach is applied to address the purpose, and a cycle time comparison between a manual application (the pick and sort tasks are performed by the operator) and a collaborative application (the pick task is performed by the operator and a cobot performs the sort task) is made based on experimental data collected from an industry relevant laboratory setup. In the remainder of this section, relevant literature with respect to the purpose is reviewed.

Literature dealing with automation related to kit preparation is scarce, but more has been done within the related areas of

assembly and warehouse order picking. In assembly systems, Barbazza et al. (2017) evaluated a fully flexible assembly system (F-FAS), consisting of feeders and an output lane, where a manipulator (robot-arm), guided by a vision system, sorted components from the feeders to the output lane. The F-FAS showed to be superior when the system output target was high. Boudella et al. (2018) modelled robotic bin picking of components for allocating SKUs in a hybrid robot-worker cell for kit preparation. The robot and the operator worked in separately and completed different parts of the kits. The model considered how empty containers and inner packing could be handled by the robot, but there was no collaboration between robot and the worker during the work cycle, and the robot did not sort the components into the kits, but instead placed them on a conveyor. Martinez et al. (2015) developed a vision system for supporting 3D bin picking of randomly oriented items. The system was capable of identifying the position of a component in the bin, and to validate that the component was picked up and placed at the right location. Caputo et al. (2018) modelled three applications of kit preparation with different automation levels: manual kitting, manual kitting supported by a picking information system, and automated retrieval with manual sorting. The model showed that automated retrieval becomes economically beneficial for higher kit production volumes. Boudella et al. (2016) discussed robotic kit preparation and highlighted three main system components: the manipulator (robot-arm), the vision system (camera), and the end-effector (gripper). In their analysis, they identified challenges with robotic kit preparation, for example selecting the correct gripper with respect to the component characteristics, and how to handle additional tasks such as removal of empty containers. Coelho et al. (2018) developed a simulation model and compared various kitting applications, some of which involved collaborative robots. Their results suggest that human workers are associated with higher productivity, but that the collaborative robots were better for dealing with uncertainty and for reducing output variability.

The remainder of the paper is organised as follows: section 2 presents a description and the aim of the study. Section 3 presents the mathematical model. In Section 4, the model is applied with experimental data collected from a laboratory setup, and the cycle times associated with the two applications are analysed and compared. Finally, the conclusions are presented in section 5.

2. DESCRIPTION AND AIM OF THE STUDY

The previous section highlighted that various applications involving robotics have been studied with respect to picking and sorting of components. Moreover, kit preparation supported by a manipulator (robot-arm) has been described and challenges with robotic-applications of kit preparation have been identified (Boudella et al., 2018; Boudella et al., 2016). However, applications of kit preparation where operators and cobots collaborate during the work cycle are scarce, but some studies suggest there is a potential of better dealing with uncertainty and reduced variability of outputs (Coelho et al., 2018). Specifically, it seems that previous research has focused on how to carry out the pick task with robotic support, but less so with respect to the sort task.

To address the current purpose, the paper develops a mathematical model for comparing the cycle time of manual and cobot-supported kit preparation. In the manual application, the pick- and the sort tasks are performed by an operator (denoted as scenario A). In the cobot-supported application, the pick task is still performed by the operator, but the sort task is performed by a cobot (denoted as scenario B). With respect to the operator's work tasks, there are no ergonomic differences aside from the sort task being removed in scenario B. The layout of the workspaces in scenarios A and B are identical, and were modelled based on the setup used by Fager (2018) for experiments on manual kit preparation. In the following, the two scenarios are described in brief. The mathematical models for estimating the cycle times of the two scenarios are developed in the next section (Section 3).

2.1. Scenario A: Manual pick and sort tasks

In scenario A, the operator performs both the pick and the sort tasks. The kit preparation area is organised as an open-ended picking aisle. To conduct kit preparation, the operator pushes a trolley with four kit containers (boxes of size 300x400x200 mm) through the aisle, always retrieving components from the left side of the trolley, see Figure 1. Each kit is designated for an assembly object, representing an individual and unique order, and holds 15 components when full. There is no requirement on the orientation and position of the components in the kits. A pick- and place-by-light system conveys instructions to the operator via light indicators and digital displays, and allows the tasks to be confirmed with button presses. The storage shelves are populated with 51 different component variants, representing 15 component families in the product structure (2-6 component variants per component family). 39 of the component variants are stored in boxes of size 200x300x200 mm in three-level flow racks, and 12 component variants are stored in boxes of size 600x800x200 mm in two-level flow racks. Each component family is composed of one or two high-runner variants (50 to 80% of the volume for the component family it is part of) and mid- or low-runner variants (10% of the volume for the component family it is part of). A complete kit contains one component from each of the 15 component families. The components are typical for automotive assembly and have varying characteristics, ranging from cords and hoses to bearings and attachments. At least one component of any variant can be grasped by one hand, and the operator can retrieve multiple components of the same SKU during a single visit to the storage container.

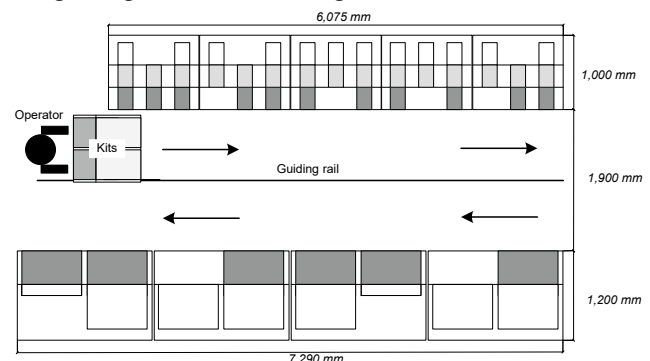


Fig. 1. Layout and movement pattern in scenario A: manual pick and sort tasks.

2.2. Scenario B: Manual pick task and cobot sort task

In scenario B, a cobot assists the operator by carrying out the sort task, while the operator performs the pick task. Here, the operator performs the pick task in the same manner as in scenario A, but instead of placing the components directly in the kits, the operator places the components in a large bin (600x800x200 mm), which acts as the collaborative zone, see Figure 2. Hence, the operator performs the pick task in scenario B in an identical fashion as in scenario A, while the sort task is greatly simplified to consist of only placing components in the collaborative zone. The cobot retrieves components from the collaborative zone and distributes them among the kit containers. The cobot is mounted on the trolley, and an electric push-assist is applied to the trolley so that the operator can push the trolley with the same speed as in scenario A. A vision system guides the cobot to perform its task correctly. The camera is mounted above the collaborative work zone and continually analyses the contents of the large bin so that the cobot never waits for the analysis to complete. The cobot retrieves components from the collaborative work zone and has three different grippers at its disposal (servo-electric 2-jaw, pneumatic, and magnetic). The cobot changes its gripper depending on the component characteristics, by accessing a tool holder positioned at its base.

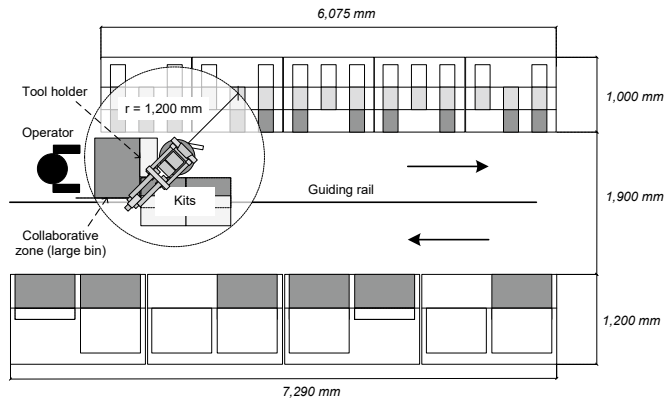


Fig. 2. Layout and movement pattern in scenario B: manual pick task and cobot sort task.

3. MATHEMATICAL MODEL

This section presents the mathematical models for estimation of the cycle times in scenarios A and B. In both scenarios, an order batch list with N order lines is completed during a picking tour. Each order line i corresponds to an SKU and specifies the quantity to pick from the shelves, and how many of the picked components should be distributed to each of the four kits.

3.1. Modelling manual pick and sort in scenario A

Since all tasks are performed manually in scenario A, the cycle time, T_A , is the same as the time spent by the operator for completing the work, T_{OP} . Hence:

$$T_A = T_{OP} \quad (1)$$

The operator's time expenditure can be estimated from the sum of the travelling time T_{travel}^{OP} , the time to pick SKUs and carry out the necessary administration related to the pick task T_{pick}^{OP} ,

in line with Battini et al. (2015), and the time to sort components among the kits and perform the necessary administration related to the sorting task T_{sort}^{OP} , in accordance with Fager (2018). Accordingly:

$$T_{OP} = T_{pick}^{OP} + T_{sort}^{OP} + T_{travel}^{OP} \quad (2)$$

The pick task T_{pick}^{OP} in (2) includes the time to receive information about the SKU (location and quantity) t_i^{SKU} , the time to search for the SKU location t_s^{SKU} , the time to pick the full quantity of the SKU t_p^{SKU} , and the time to perform the pick-from confirmation of the SKU t_c^{SKU} .

Receiving SKU information (t_i^{SKU}), searching for the SKU (t_s^{SKU}), and carrying out a pick-from confirmation (t_c^{SKU}), is performed once per order line i for all order lines in the current picking tour (N). The time to pick the full quantity of SKU i depends on the quantity to pick (as picking more components at once will require counting of the components and more handling), and the pickability of the components (the ease by which components can be grasped and separated from other components in the storage container). With respect to the quantity to pick, picking a single component requires time t_{p,q_s} , while picking additional components require the additional time t_{p,q_a} for each additional component. Pickability accounts for when the components stick to each other inside the storage container – as is typical with, for example, springs – or for components that are difficult to grasp, which will require more time for the pick activity (Hanson and Medbo, 2016). Pickability is here represented by the binary variable p , where $p = 1$ means normal pickability (components can be grasped without difficulty) and $p = 0$ means low pickability (components stick to each other or are difficult to grasp properly), and p_i has to be determined for each SKU i . The additional time requirement for an SKU with low pickability is represented by α .

From the above, the time spent by the operator on performing the pick task T_{pick}^{OP} can now be estimated as:

$$T_{pick}^{OP} = N \cdot (t_i^{SKU} + t_s^{SKU} + t_c^{SKU}) + \sum_{i=1}^N (t_{q_s}^P + t_{q_a}^P \cdot (q_i - 1) + \alpha \cdot (1 - p_i)) \quad (3)$$

The sort task T_{sort}^{OP} in (2) includes the time to receive information about in which kits to place components and what quantity of components to place in each kit t_i^{kit} , the time to search for the kit container t_s^{kit} , the time to place components in kits t_p^{kit} , and the time to perform place-to confirmations t_c^{kit} . Receiving information about the kits (t_i^{kit}) and searching for and identifying the kit containers to place the components in (t_s^{kit}) occurs once per order line i for all order lines in the picking tour (N). When sorting components, the operator places the components one at a time in the kit containers, and performs the place-to confirmation before placing components in the next kit. After placing the first component $t_{p,f}^{kit}$, the operator is already next-by the remaining kit containers, why subsequent placements require less time $t_{p,a}^{kit}$. The place-to confirmation time t_c^{kit} is performed once per kit every time a component is placed there.

From the above, the time to carry out the sort task T_{sort}^{OP} can now be estimated as:

$$T_{sort}^{OP} = N \cdot (t_I^{kit} + t_S^{kit}) + \sum_{i=1}^N (t_{p,f}^{kit} + (q_i - 1) \cdot t_{p,s}^{kit} + t_C^{kit} \cdot q_i) \quad (4)$$

The time spent on travelling T_{travel}^{OP} in (2) is estimated from the distance covered during the picking tour, which is the sum of the lengths of the shelves $\sum l_s$ and the average travelling speed v_{OP} . However, some of the travelling time can be carried out while other tasks are performed, for example receiving SKU information and searching for the SKU location. Here, it is assumed that the operator moves the trolley one shelf at a time for all shelves N_s , and information can be received t_I^{SKU} , and the SKU location can be searched for t_S^{SKU} , for the first SKU in each shelf. The trolley must also be started t_s and parked t_p in addition to the travelling time. Each shelf j has length $l_{s,j}$. Accordingly:

$$T_{travel}^{OP} = S \cdot (t_s + t_p - (t_I^{SKU} + t_S^{SKU})) \cdot \sum_{j=1}^S \frac{l_{s,j}}{v_{OP}} \quad (5)$$

The operator cycle time can now be estimated from (2) with (3), (4), and (5), and the cycle time of scenario A is given in accordance with (1).

3.2. Modelling manual pick and cobot sort in scenario B

Robot-supported picking has been modelled before (see e.g. Boudella et al., 2018), but the sort task related to kit preparation has not yet been considered in previous research. Here, a combination of the reasoning presented by Boudella et al. (2018) and observations from the laboratory setup are applied in the model development for cobot-supported sorting. With scenario B, the operator and the cobot work collaboratively. Here, the cycle time will depend on how well the collaboration works. For each order line i , the operator will carry out the pick task. Once the operator has dropped the components in the collaborative zone, the cobot will begin distributing the components into the kits. While the cobot is at work, the operator will perform the next pick task, for order line $i + 1$. If the operator finishes the pick task before the cobot has sorted the components of the previous order line, the operator has to wait for the cobot to finish. Similarly, if the cobot finishes before the operator, the cobot has to wait. For the first order line $i = 1$, the cobot will idle as the collaborative zone is empty, and for the last order line, the operator will idle as all $i = N$ SKUs have already been picked. Hence, the cycle time of scenario B will be given by:

$$T_B = T_{B_1}^{OP} + T_{B_N}^{CB} + \sum_{i=2}^{N-1} T_{B_i} \quad (6)$$

where,

$$T_{B_i} = \max(T_{B_{i+1}}^{OP}, T_{B_i}^{CB}) \quad (7)$$

The time spent by the operator and the cobot on the collaborative task (placing components in the collaborative zone by the operator; retrieving components from the collaborative zone by the cobot) are represented by T_{collab}^{OP} and T_{collab}^{CB} , respectively. The operator's time requirement in scenario B is given by:

$$T_B^{OP} = T_{pick}^{OP} + T_{travel}^{OP} + T_{collab}^{OP} \quad (8)$$

The time spent for carrying out the pick task T_{pick}^{OP} and the travelling time T_{travel}^{OP} in (8) are estimated in the same manner as in (2) for scenario A, from (3) and (5). Although the operator is relieved of the sorting task in scenario B, the operator must still drop the picked components in the collaborative zone, represented by T_{collab}^{OP} . Observations from the laboratory setup suggest that the time for placing components in the collaborative zone is proportional to the quantity, and placing the first component t_f^{collab} takes longer time than placing subsequent ones t_s^{collab} . Although there is no requirement on positioning of the components within the collaborative zone, the operator must still separate the components from each other so that the vision system can correctly identify them. Moreover, there is no need to perform a place-to confirmation since all components are placed in the same compartment. Hence:

$$T_{collab}^{OP} = \sum_{i=1}^N t_f^{collab} + t_s^{collab} \cdot (q_i - 1) \quad (9)$$

The operator's time requirement in scenario B can now be estimated from (8), with (3), (5), and (9).

In scenario B, the cobot's time requirement is estimated based on Boudella et al. (2018) as:

$$T_B^{CB} = T_{travel}^{CB} + T_{vision}^{CB} + T_{tool}^{CB} + T_{sort}^{CB} + T_{collab}^{CB} \quad (10)$$

Here, the travel time of the cobot will always correspond with the travel time of the operator, but the cobot can always work while travelling. Hence, in scenario B, the cobot's travel time is always zero. Furthermore, since the vision system is mounted above the collaborative zone, image processing can happen continually and the T_{vision}^{CB} will always be zero. The tool changing time T_{tool}^{CB} is the same for all tool changes, but depends on whether SKU $i + 1$ requires the same tool as SKU i . This is evaluated in the parameter $\theta(i)$, which is 1 when no tool change is required and 0 if a tool change is required. Moreover, the cobot always starts with the correct tool for the first order line $\theta(1) = 1$. Accordingly:

$$T_{tool}^{CB} = t_{tc} \cdot \sum_{i=2}^N (1 - \theta_i) \quad (11)$$

When retrieving components from the collaborative zone T_{collab}^{CB} , the failure rate of picking the component on the first try ε depends on the type of gripper and the component characteristics (Boudella et al., 2018). The gripping time t_g is the same for any component gripped successfully on the first try with the same tool. Hence, the picking time in the collaborative zone:

$$T_{collab}^{CB} = t_g \cdot \sum_{i=1}^N (q_i \cdot (1 + \varepsilon_i)) \quad (12)$$

The time required by the cobot for the sort task depends on in which kit container the placements are made. It is assumed that the cobot moves each component from the centre of the collaborative zone to the centre of kit container j in a straight line of distance d_{kit_j} . Each kit j of all kits in the batch M should receive $q_{kit_i,j}$ components of SKU i . The time for

placing a component into a kit container t_p^{CB} is the same for all components and gripper types. The move speed of the cobot is lower in the collaborative zone (v_{CBin}) than outside the zone (v_{CBout}), for safety reasons. Moreover, the cobot always returns the same way to the collaborative zone after sorting a component. Accordingly:

$$T_{sort}^{CB} = \sum_{i=1}^N \left(\frac{2 \cdot d_{in}}{v_{CBin}} + \sum_{j=1}^M \frac{2 \cdot q_{kit_{i,j}} \cdot d_{kit_j}}{v_{CBout}} + t_p^{CB} \cdot q_i \right) \quad (13)$$

The cobot’s time requirement in scenario B from (10) can now be estimated with (11), (12), and (13). The cycle time of scenario B is estimated from (6) and (7) with (8) and (10).

4. MODEL APPLICATION AND COMPARISONS

To carry out the cycle time comparison of scenarios A and B, the model was applied with experiments data from relevant previous studies (e.g. Fager, 2018; Boudella et al., 2018; Battini et al., 2015). The parameters for manual picking activities in scenarios A and B were estimated based on earlier experiments dealing with manual picking from Fager (2018) and Battini et al. (2015). The parameters for cobot picking activities were estimated based on Boudella et al. (2018), and on discussions with a cobot developer. The experimental values showed in Table 1 were used in the application.

As input to the model, 1,000 batch order lists (batch size was four kits) were generated randomly, based on the distributions of high-, medium-, and low-runners within the component families (see section 2.1). In the following, the time allocation between tasks are presented for scenarios A and B in section 4.1, and the comparison of the cycle time between the two scenarios is presented in section 4.2.

4.1 Time allocation in scenarios A and B

With manual pick and sort tasks in scenario A, the operator spends most of the time on the pick and sort tasks (50% and 42% respectively). Only about 8% of the time is spent on travelling, as the preparation area is relatively dense, and the operator can search for components while travelling.

In scenario B, when the cobot performs the sort task, the operator has fewer activities to carry out, and most of the operator’s time is spent on activities related to the pick task (77%). The time spent by the operator on the collaborative task is 11%, and the time spent on travelling is still small (12%), due to the high density of the picking area.

The cobot spends more than half of its time (61%) on the sort task, by placing components one at a time in the kits. The tool change time make up 13% of the time, and the proportion of time spent on the collaborative task – retrieving components from the collaborative zone – is 26%.

Table 1. Experimental values used in the model application.

Description	Value
S Number of shelves at the kit preparation area	9
l_{S_i} Length (m) of shelf i	[1.2, 1.7]

t_I^{SKU} Time (s) for receiving SKU information (light indicators)	0
t_S^{SKU} Time (s) for searching for an SKU (light indicators)	1.37
$t_{q_s}^P$ Time (s) for picking a single component	1.12
$t_{q_a}^P$ Time (s) per component for picking ($q_i - 1$) additional components	0.52
α Time (s) addition for picking SKU with low pickability	0.58
t_C^{SKU} Time (s) for pick-from confirmation (button press)	1.01
t_I^{kit} Time (s) for receiving kit information (light indicators)	0
t_S^{kit} Time (s) for searching for the kits (light indicators)	0.75
$t_{P,f}^{kit}$ Time (s) for placing the first component in a kit	0.66
$t_{P,s}^{kit}$ Time (s) per component for placing ($q_i - 1$) subsequent components in kits	0.57
t_C^{kit} Time (s) for performing a place-to confirmation	0.87
t_s Time (s) for starting the trolley	0.2
t_p Time (s) for parking the trolley	0.2
v_{OP} Travelling speed (m/s) of the operator with the trolley	1.1
t_f^{colla} Time (s) for placing the first component in the collaborative zone	0.66
t_s^{colla} Time (s) per component for placing ($q_i - 1$) subsequent components in the collaborative zone	0.25
t_{tc} Time (s) for the cobot to perform a tool change	2
t_g Time (s) for the cobot to grip a component in the collaborative zone for different tool types	[2, 1, 1.2]
ϵ_i Failure rate (percentage) of the cobot when gripping component i with different tool types	[5, 1, 1]
v_{CBin} Linear move speed (m/s) of cobot within the collaborative zone	0.3
v_{CBout} Linear move speed (m/s) of cobot outside the collaborative zone	0.9
d_{in} One-way distance (m) moved by cobot within collaborative zone	0.3
d_{kit_j} Distance (m) between the collaborative zone and kit container j	[1.1, 0.6, 0.9, 0.4]

4.2 Cycle time comparison

Figure 3 shows a comparison of the average cycle time of scenarios A and B when the same 1,000 batch order lists are completed in the model application. From Figure 3, it is clear that the average cycle time is higher in scenario B (272 seconds) than in scenario A (267 seconds). This was also confirmed with a statistical comparison of the means ($p < 0.05$). However, Figure 3 also shows that the standard deviation of the cycle time in scenario A (11.4 seconds) is higher than in scenario B (6.7 seconds). The higher cycle time

in scenario B can be explained by a combination of the cobot's movement speed and that it only can handle a single component at a time, compared with the operator. The lower variability of the cycle time in scenario B is likely due to the collaboration between the operator and cobot, where the two parties balance each other's workload, in accordance with (6) and (7).

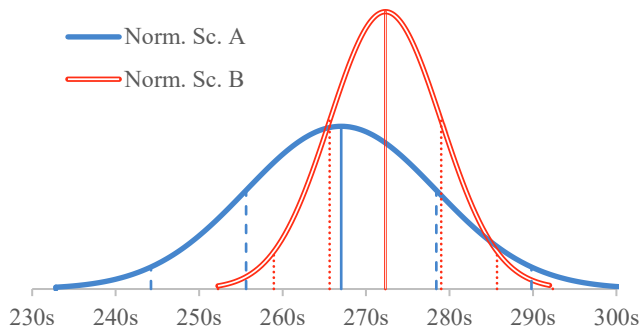


Fig. 3. Comparison of the cycle time distribution of scenarios A (blue solid line) and B (red double line) from the model application. The continuous vertical line of each colour indicates the average cycle time for 1,000 randomly generated batch order lists; the dashed (scenario A) and dotted (scenario B) vertical lines of each colour indicate standard deviations from the average ($\pm 3 \cdot \sigma$).

5. CONCLUSIONS

This paper has modelled and compared kit preparation when the work is performed manually, with an application where the work is performed collaboratively by an operator and cobot, where the cobot carried out the sort task. The comparison was made with respect to the cycle time, which is central for industrial application of kit preparation. The findings suggest that the use of cobots to support the sort task in kit preparation offers a slightly higher, but also a more stable, cycle time. A more stable cycle time can contribute to easier planning of the work load, less need to hold inventory, and less risk of the kit preparation process to cause production delays due to inconsistently timed deliveries.

The modelling approach applied in the paper made use of experimental data collected from a laboratory setup. A limitation of the approach is that the model is a simplification of an industrial setting, and there may be other aspects not covered by the model that can hinder implementation. For example, there may be unsuitable component characteristics for cobot picking (see e.g. Boudella et al., 2018), or different safety regulations compared with a laboratory environment, since other people than the operator may be present at the preparation area. A comprehensive analysis must therefore be carried out before implementation is considered.

The paper's theoretical contribution consists of the modelled application for cobot-supported kit preparation. This is important because full automation of industrial tasks is often in focus in the literature, while collaborative applications have been relatively rare. Managers may use the model to assess whether a cobot-supported kit preparation may be feasible in

their own systems. Future research should explore how variables can affect the comparison, for example, if an autonomous carrier can be used to help guide the picker to the correct SKUs, the effect of batch size, or if the collaborative zone can be divided into compartments to better absorb variability between operator and cobot. Aside from efficiency, future research should also consider how collaborative applications affect other performance areas of kit preparation, for example, quality, flexibility, ergonomics, and cost.

REFERENCES

- Barbazza, L., Faccio, M., Oscari, F. and Rosati, G. (2017). "Agility in assembly systems: a comparison model", *Assembly Automation*, 37(4), 411-421.
- Battini, D., Calzavara, M., Persona, A., & Sgarbossa, F. (2015). "A comparative analysis of different paperless picking systems", *Industrial Management & Data Systems*, 115(3), 483-503.
- Boudella, M. E. A., Sahin, E. and Dallery, Y. (2018). "Kitting optimisation in Just-in-Time mixed-model assembly lines: assigning parts to pickers in a hybrid robot-operator kitting system", *International Journal of Production Research*, 56(16), 5475-5494.
- Boudella, M. E. A., Sahin, E. and Dallery, Y. (2016). "A mathematical model to assess the performance of a robotic kitting system in an assembly plant". In *proceedings of the 11th International Conference on Modeling, Optimization and Simulation*, Aug 2016, Montréal, Canada.
- Caputo, A. C., Pelagagge, P. M., & Salini, P. (2018). "Economic comparison of manual and automation-assisted kitting systems", *IFAC-PapersOnLine*, 51(11), 1482-1487.
- Coelho, F., Relvas, S. and Barbosa-Póvoa, A. P. (2018), "Simulation of an order picking system in a manufacturing supermarket using collaborative robots", *Proceedings 32nd European Conference on Modelling and Simulation*, May 22-25, Wilhelmshaven, Germany.
- Fager, P. (2018). "Kit preparation for mixed-model assembly: efficiency impact of confirmation methods", *Industrial Management & Data Systems*, <https://doi.org/10.1108/IMDS-07-2018-0287>
- Hanson, R., & Medbo, L. (2016), "Aspects influencing man-hour efficiency of kit preparation for mixed-model assembly", *Proceedings of the 6th CIRP Conference on Assembly Technologies and Systems (CATS)*, Amsterdam: Elsevier, 353–358.
- Martinez, C., Boca, R., Zhang, B., Chen, H. and Nidamarthi, S. (2015), "Automated bin picking system for randomly located industrial parts", *Proceedings of the 2015 IEEE International Conference on Technologies for Practical Robot Applications (TePRA)*, 11-15 May, Woburn, USA.
- Medbo, L. (2003), "Assembly work execution and materials kit functionality in parallel flow assembly systems", *International Journal of Industrial Ergonomics*, 31(4), 263-281.
- Sadrifaridpour, B. and Wang, Y. (2018), "Collaborative Assembly in Hybrid Manufacturing Cells: An Integrated Framework for Human-Robot Interaction", *IEEE Transactions on Automation Science and Engineering*, 15(3), 1178-1192.