Exploiting the potential of human-machine work systems

A hybrid cycle time determination model considering system parameters influencing cycle time

Titanilla Komenda, Fraunhofer Austria Research GmbH, Wien (Austria), titanilla.komenda@fraunhofer.at

Maximilian Schelle, Fraunhofer Austria Research GmbH, Wien (Austria), maximilian.schelle@fraunhofer.at

Felix Kamhuber, Fraunhofer Austria Research GmbH, Wien (Austria), felix.kamhuber@fraunhofer.at

Sebastian Schlund, Technische Universität Wien, Wien (Austria), sebastian.schlund@tuwien.ac.at

Abstract: Even though human-machine work systems seem to be a promising approach in closing the economic efficiency gap between manual production and automation, the installation rate of such kind of systems is still low. This is based on the general opinion that cycle time is only achievable on the basis of the machine's velocity. However, the velocity of a robot is often limited due to prevailing safety guidelines. In the present work, it is therefore investigated what system parameters influence cycle time in a human-machine work system and how transparency can be created so as to increase planning reliability. Based on a hybrid model approach, it is shown how the modelling of human-machine work systems can be carried out taking into account system parameters that influence cycle time. The application of the developed hybrid cycle time model is shown and validated on a circuit board packaging process.

1 Motivation and Problem Formulation

The global demand for variable batch sizes and customised product variants call for flexible production systems capable of meeting these requirements (Monostori et al. 2016). Human-machine work systems can be an enabler to this, by taking advantage of both, the robots' and humans' respective capabilities (Ranz et al. 2017). According to the International Federation of Robotics (IFR 2020), as an international umbrella organisation of all national industrial and research robotics associations, the implementation of industrial robotics systems has increased by an average of 11 %

annually since 2014 (with the exception of 2019). Compared to industrial robot systems, the share of collaborative robot systems is just under 5 %, although an increase in the installation rate of 15 % was identified in the years 2017-2019. According to a recent survey by Karlsruhe University of Applied Sciences, the use of collaborative robots in the context of work systems with human-robot collaboration is mainly suitable for reducing ergonomically stressful or monotonous work steps – an improvement in cycle time cannot be achieved (Hornung 2021). In this context, the lack of improvement in cycle time is cited as one of the major disadvantages of work systems with human-robot collaboration, which is also considered as one of the main reasons for the inhibited introduction of the concept of human-machine collaboration and thus of collaborative robots, in addition to the lack of knowledge on effective implementation.

However, the concept of human-machine collaboration would close the economic efficiency gap between purely manual production and robot- or machine-assisted production and thus make production in high-wage countries more competitive (Matthias und Ding 2013). What is unclear, are the quantifiable marginal lot sizes for the economic use of work systems with human-machine collaboration. Added to this is the lack of knowledge about the influence of system parameters. In particular, cycle time determination is usually based on the safety mode of the machine – and thus on its safety-compliant or permissible movement speed (ABB 2014). It is therefore assumed that cycle time determination is a two-dimensional problem whose solution leads to the achievement of the minimum productivity requirements.

However, by closely linking humans and machines, workflow organisation, cycle time prediction and cost estimation get more complicated due to mutually influencing system parameters and with this, trade-offs in the specified objectives. Hence, a simple to use simulation-based optimisation framework is required to effectively exploit potentials of human-machine work systems by enabling an automated comparison of system configurations based on different system parameters influencing cycle time.

The research question at hand focuses on how the planning reliability with regards to cycle time determination in human-machine work systems can be increased by creating transparency of system parameters influencing cycle time at the same time.

2 State of the Art in Cycle Time Determination

Due to spatial separation of humans and machines and the associated separation of tasks, the design of automated work systems and the design of manual work systems were considered separately. As a result, methods for determining cycle times for manual and automated tasks were also developed separately and are different. In the following, state of the art methods of cycle time determination are first listed on the basis of planning methods in the areas mentioned, in order to finally refer to methods in the field of research that already include aspects of a holistic consideration of humans and machines in a single approach.

Wloka (2013) determines cycle times of automated tasks by modelling and simulating the robot system’s behaviour. For this purpose, the structure of the robot manipulator, the control behaviour as well as the work system design including the arrangement of peripheral devices are described in a model. The cycle time determination model is therefore composed of a kinematics model, a geometry model, a control model and a simulation model. The geometry model contains all information regarding the external shape of the robot and peripheral devices in the work system. The kinematics model describes the spatial position of the individual joints of the robot during the execution of a specific robot path. The control model is used for the characteristic description of the robot's movement behaviour, such as maximum travel ranges, speeds and accelerations. In addition to communication interfaces, control properties are described in an algorithmic model component. The simulation model ultimately includes further simulation-specific model components, such as the visualisation of gripping processes.

Bokranz and Landau (2012) determine cycle times of manual tasks through process time modules, so-called Methods-Time Measurement (MTM) modules. MTM was developed in America in the 1950s and is based on empirically determined studies of manual work performance, in which the determined process times for specified activities were summarised in the form of tables. In the application of MTM, all movements performed by humans are traced back to certain basic movements (such as grasping, joining, releasing and walking) for which the required times are specified. Building on the MTM method, condensed methods have also been derived that combine the basic movements (e.g. "pick up and place", consisting of "reach, grasp, bring, join and release") and thus enable a faster and often also sufficiently accurate analysis of manual work processes. The most common condensed systems are MTM-UAS (Universal Analysing System) for series production and MTM-MEK (MTM in individual and small series production). According to Kuhlang (2015), MTM can also be applied to transfer partial operations that have led to an overall negative assessment of manual work to machine activities – leading to an approach to task sharing in the context of collaborative activities.

Schröter et al. (2016) defined an approach for describing robot movements based on the MTM process time modules. These so-called RTM (Robot Time and Motion) building blocks contain five categorical elements, i.e. movement (reaching, moving, orienting), measuring (stopping the movement due to a sensor signal or force overshoot, information about touch or camera), grasping (picking up and placing), delay (process-specific delays or waiting times) and movement type (linear, point-to-point). With the help of the RTM modules, it is now possible to define tasks in collaborative human-machine work systems already in the planning phase with the help of a description formalism. Due to the similarity to the MTM building blocks, different task division variants can also be quantifiably compared with each other. However, the accuracy of the RTM time blocks is not satisfactory, especially for point-to-point movements of the robot, as it is strongly dependent on the control model of the respective robot system.

Gombolay et al. (2013) considered a mutual influence of temporal and spatial constraints in human-robot work systems. They demonstrate real-time task assignment and scheduling in collaborative human-machine work systems using a custom algorithm called Tercio. Tercio takes a set of tasks, temporal interval constraints, a number of agents and an objective function as input parameters. The algorithm then first computes an optimal agent assignment by solving a mixed integer problem (MIP) that contains constraints for balancing per-agent workload. Based on the agent assignment and task structure, Tercio then allocates tasks using an analytical test such that all time constraints are satisfied. Once the schedule satisfies the time constraints, agent and space resource sequencing constraints are added to the problem.

Pellegrinelli and Pedrocchi (2018) extended this approach to include the influence on the robot's motion behaviour when humans are in temporal and spatial proximity. They assume that the robot changes its movement behaviour as soon as the human enters the workspace or comes too close to the robot. In this case, the robot will not necessarily stop its movement, but will avoid the human and thus dynamically adapt its planned movement path to the local proximity of the human. For this reason, cycle time estimation of machine behaviour in the planning phase is no longer possible with conventional methods, as it depends on the specific system and resource conditions. Pellegrinelli and Pedrocchi now followed the approach of a workspace segmentation taking into account the volume of space occupied by the human and the robot during the movement. This segmentation is then used to define a set of Markov chains that describe the human-robot interaction and allow the estimation of the robot execution time.

Bänziger et al. (2018) take a similar approach to Gombolay et al. (2013). However, they use a genetic algorithm for task assignment and scheduling and describe the tasks based on MTM building blocks extended by the number of repetitions within a process. Furthermore, the model also contains information on the ergonomics of work execution. Based on a two-dimensional simulation, the local relationships of individual resources are visualised and necessary times for the resulting movement paths are calculated. To determine the optimal task assignment, the minimum cycle time is then calculated as a function of process times, waiting times and movement times based on distances to be covered, which are provided with weighting factors.

State of the art cycle time determination approaches focus on system parameters such as motion speed or task execution speed of humans and robots, their spatial relation as well as task allocation patterns but do not consider the mutual influence of those parameters in one holistic approach. Especially the dynamic change of the robot's motion speed dependent on the temporal and spatial proximity between human and robot (in order to apply with current safety regulations) are not considered. In addition, conventional planning methods also do not consider individual performance levels of humans which can be an essential benefit of the adaptive robot control with regards to human-centric planning approaches. Therefore, a cycle time determination model must consider the mutual influence of system parameters and their impact on cycle time.

3 Cycle Time Determination Model

A human-machine work system can be considered as a hybrid model consisting of both discrete and continuous elements. While the motion behaviour of humans and machines can be considered as a continuous process, specific properties changing for example the robot's velocity can be considered as discrete events. This way, a human-machine work system can be modelled as a hybrid system model with discrete and continuous model parts that influence each other depending on the specified conditions. Thus, a hybrid system model approach was used to simulate the motion behaviour of the individual resources, i.e. humans and machines, in the human-machine work system. The motion behaviour then results in execution times of individual tasks which finally leads to a cycle time.

Zeigler et al. (2000) defined a modular, hierarchical formalism for modelling and analysing discrete event systems (Discrete Event System Specification), which also includes a formulation of continuous systems (Differential Equation Specified System) and a description formalism for hybrid systems, the so-called DEV&DESS formalism (Discrete Event and Differential Equation Specified System). The model concept includes the combination of a discrete (DEVS) and a continuous (DESS) component, which can influence each other. Pawletta et al. (2006) eventually implemented this description formalism in a toolbox in MATLAB®, which allows hybrid models to be simulated on the basis of modified discrete models with additional continuous model behaviour. This modified discrete event simulator solves ordinary differential equations between individual events to generate the continuous model behaviour (Heinzl 2020). The toolbox applies an ODE wrapper approach with the MATLAB® integrated ODE45 solver based on Runge Kutta with variable step size.

In addition, the MatlabDEVS toolbox uses the object-oriented programming of MATLAB® both for the implementation of the DEVS simulation environment and for the definition of the simulation model. The simulation model can be composed of sub models (objects) of different types (classes). By using a discrete simulator and a mapping of model elements to objects (instances), the information of the hierarchical model structure is preserved during the simulation and thus enables the simulation of the dynamic system behaviour (Deatcu and Pawletta, 2012). Thus, the hybrid system model of the human-machine work system was implemented as a hybrid simulation model consisting of individual hybrid resource models, i.e. sub models, of different types, i.e. humans and machines, which are instantiated by a specific resource class but with individual attributes and properties. The motion behaviour of those hybrid resource models was then modelled based on a uniformly accelerated motion with a trapezoidal velocity profile with an acceleration phase, a deceleration phase of equal size as well as a phase with constant velocity. Consequently, the cycle time is determined based on

$$t = \sum_{\tau=1}^{m} \sum_{r=1}^{n} x_{\tau r}\, t_{\tau r} \tag{1}$$

where m is the number of tasks τ and n is the number of resources r, while $x_{\tau r}$ defines the task allocation to a specific resource. In addition, one task can only be allocated once to a resource while all tasks have to be allocated to at least one resource

$$x_{\tau r} \in \{0,1\} \quad \forall \tau = 1, \dots, m, \quad \forall r = 1, \dots, n \tag{2}$$

$$\sum_{r=1}^{n} x_{\tau r} = 1 \quad \forall \tau = 1, \dots, m \tag{3}$$

while the task execution time by a specific resource is given by

$$t_{\tau r} = \frac{v_r^2 + a_r s_{\tau r}}{a_r v_r} \tag{4}$$

which can be determined on the basis of the resource velocity v_r and the resource acceleration a_r, where the travelled distance $s_{\tau r}$ to perform the task τ by the resource

r is defined by the distance travelled in the acceleration and deceleration phase s_{b} and the constant speed phase s_{vk}

$$s_{\tau r} = s_{\mathrm{b}} + s_{\mathrm{vk}} + s_{\mathrm{b}} = 2s_{\mathrm{b}} + s_{\mathrm{vk}} \tag{5}$$

If the task execution time determined this way is set in relation to the task execution time without an acceleration phase $\tilde{t}_{\tau r}$ – e.g. applied in the isolated model – the model quality of the hybrid model with a trapezoidal velocity profile can be determined in comparison to that simplified motion model

$$\frac{t_{\tau r}}{\tilde{t}_{\tau r}} = \frac{\frac{v_r^2 + a_r s_{\tau r}}{a_r v_r}}{\frac{s_{\tau r}}{v_r}} = \frac{\frac{v_r^3}{a_r} + v_r s_{\tau r}}{v_r s_{\tau r}} = 1 + \frac{v_r^2}{a_r s_{\tau r}} \tag{6}$$

The same applies to the comparison with higher-order s-curve models.

4 Critical system parameters

A crucial part in human-machine work systems is the technical work organisation as it opens up a complex field of planning issues due to the constant probabilistic interaction scenarios of humans and machines. Those interaction scenarios influence the spatial and temporal relation between humans and machines, thus the motion behaviour of those entities and thus influence cycle time.

Thus, one critical system parameter is the layout of the work system. By spatially dividing the work areas of humans and machines, the distances between humans and machines can be increased, which increases safety (in terms of duration of exposure to a potential hazard) as well as cycle time since longer distances have to be covered to execute potential collaborative tasks or handover-tasks. Furthermore, different types of interaction scenarios require different safety principles which again influence cycle time. They can go from stopping a machine if a human is in a specific distance to the machine, to dynamically adapting the machine’s velocity as a function of the human’s proximity, towards determining a safety-rated velocity of the machine so as to not exceed pre-defined biomechanical force and pressure limits during a possible collision between humans and machines. The different safety requirements also lead to different requirements in modelling accuracy with regards to the physical and dynamic behaviour of humans and machines.

Besides safety, the definition of interaction scenarios also refers to the task or resource allocation problem. Here, not only the temporal and spatial relation between humans and machines changes with different task allocation patterns but the execution time of a task can also change dependent on the allocated resource. This is not only dependent on the resource’s distance at the time of task allocation but also on its individual properties, e.g. humans with different performance levels or dynamically changing performance levels due to fatigue.

5 Model Application and Validation

The cycle time determination model was applied on the design of a human-machine work system for the implementation of a PCB packaging process consisting of six different tasks, i.e. (1) scanning, (2) packaging, (3) tray handling, (4) lid handling, (5) container handling and (6) labelling. Those tasks were allocated to either one or two resources resulting in different system variants with six different task allocation patterns from fully manual (pattern A) to semi-automated (pattern B-E) to fully automated (pattern F) task execution. Furthermore, humans with five different performance levels were considered as well as robots with three different safety modes. Thus, three different system parameters, i.e. task allocation, human performance level as well as robot safety mode, alone led to 68 theoretically possible work system variants. The application of the cycle time determination model shows different cycle time values for the identified 68 system variants (Fig. 1).

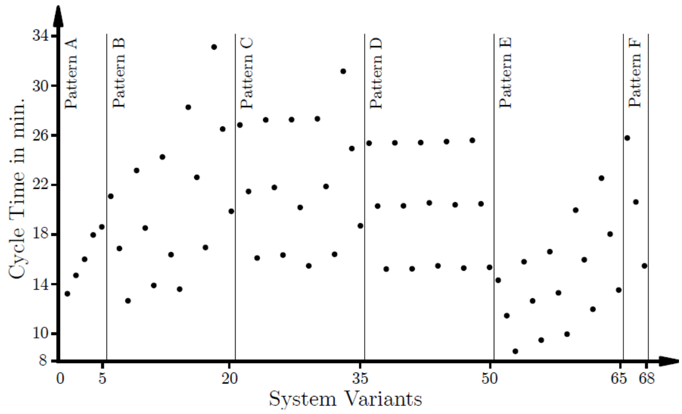

Figure 1: *Cycle time values for different system variants of the PCB packaging process*

The cycle time was calculated based on a packaging process of a full container containing 216 PCBs. The cycle time values reach from a minimum cycle time of 8.58 min. to a maximum cycle time of 33.12 min. which results in an average cycle time of 20.85 min. ± 12.27 min. corresponding to a scattering of ± 59 % of the overall cycle time values.

Tab. 1 shows the comparison of the cycle time values for one real system variant and the values determined with the methods MTM, a conventional simulation model with isolated models of humans and machines as well as with the hybrid model approach considering the mutual behaviour influence of resources.

Table 1: *Comparison of cycle time values based on different determination methods*

Real System	Hybrid Model	Conventional Model	MTM
15 min.	15.80 min.	16.17 min.	18 min.
100 %	105.3 %	107.8 %	120 %

6 Conclusion and Outlook

The state of the art demonstrates that there are many ways to consider human-machine interaction and collaboration and thus determine cycle time in the planning phase of human-machine work systems. The hybrid model approach based on the DEV&DESS-formalism seems to be more accurate than currently applied methods as the consideration of discrete and continuous components in the simulation model leads to a more realistic system behaviour as it considers dynamically changing human-machine interaction. The applied approach with a simplified motion behaviour representation of humans and machines based on trapezoidal velocity profiles already showed an impact. Compared to methods such as MTM or conventional simulation models with isolated model behaviour, an increased accuracy of 5.3 % in terms of the determined cycle time could be achieved. With a targeted production rate of 2.7 Mio. pieces per year this could make a difference of around 50,000 PCBs or 231 containers per year.

Even though, the needed accuracy of the cycle time is highly dependent on the implemented motion behaviour model of the simulated entities, a simulation-based optimization could help in an automatic comparison of different system variants in terms of cycle time. Accordingly, we are working on building a scalable hybrid simulation model that can consider multiple resources with different motion characteristics. Thus, the PCB packaging process might also be conducted by multiple resources such as humans, mobile robots and stationary robots with individual motion characteristics. System variants could go from manual and rigidly linked work system designs to flexible and reconfigurable layouts (Fig. 2). Especially for the reconfigurable system variants, the simulation defines an initial state for humans and machines, where the preparation and post-processing times are set accordingly generous (worst case), while allocated tasks can be executed consecutively or independently of each other (in parallel) under certain conditions. Reconfigurable system variants make the optimization problem dependent on the spatial resolution of the defined collaborative workspace. However, an initial solution is optimized step by step by a GA, which on the one hand can change the task assignment (from human to machine and vice versa) and on the other hand can reschedule the start times for each task. We are currently in the process of building and validating the simulation in combination with the GA for the presented system variants.

The results of our research show that there is need for further investigation in modelling hybrid human-machine work systems. As discussed, there is strong interconnection between the timing, trajectory, humans' individual behaviour and the layout in a human-machine work system. With the development of a simulation-integrated optimization tool, a sensitivity analysis can be achieved identifying the most crucial system parameters when it comes to specific system requirements. Furthermore, optimization might help to identify the most resilient work system variant where changing individual entities have little impact on the cycle time or other objectives.

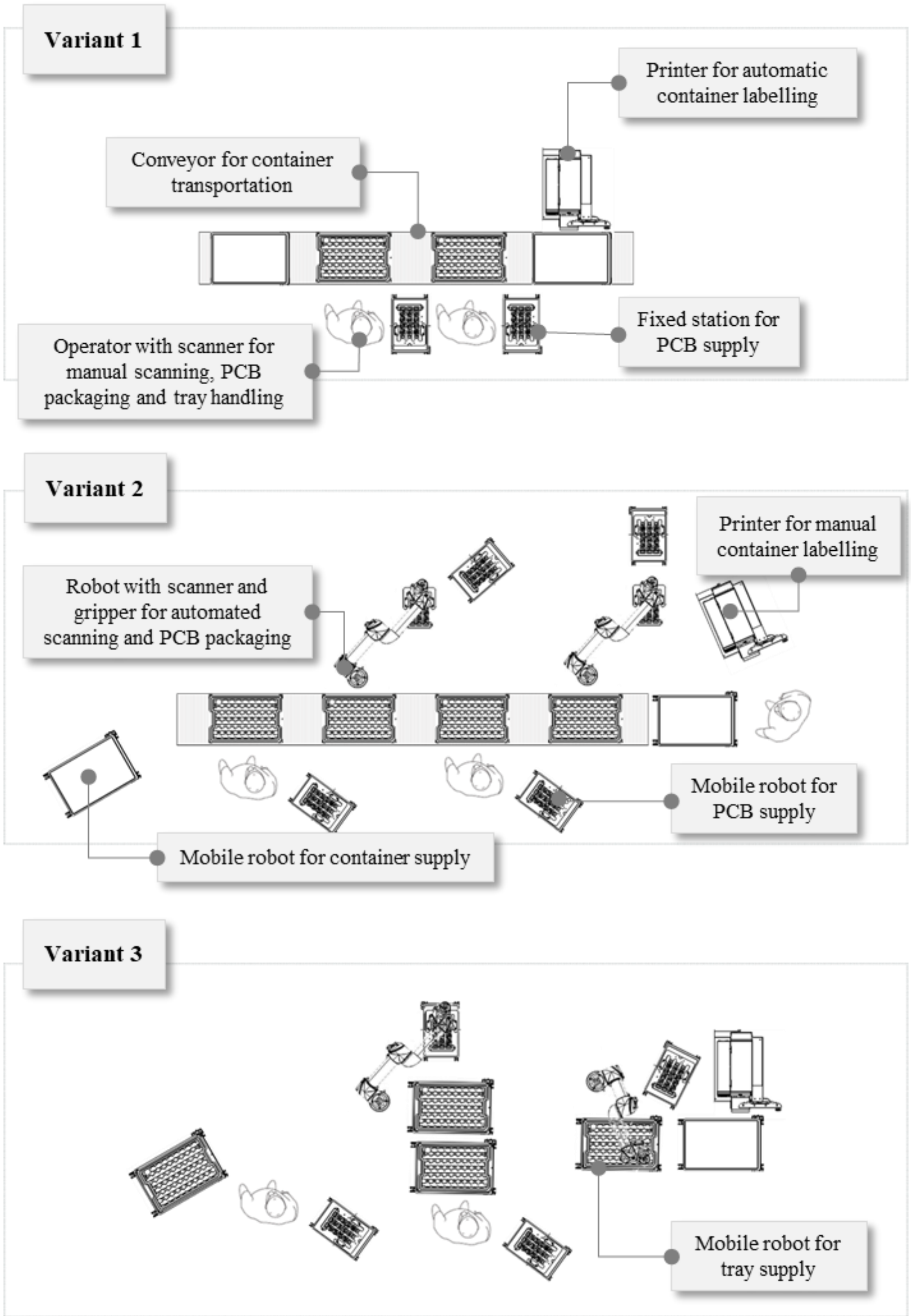

Figure 2: *Scalable system variants for the PCB packaging process*

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