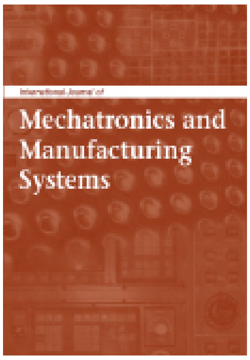

International Journal of Mechatronics and Manufacturing Systems

ISSN online: 1753-1047 - ISSN print: 1753-1039
https://www.inderscience.com/ijmms

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DOI: 10.1504/IJMMS.2023.10062522

Article History:

Received:	15 February 2023
Last revised:	30 June 2023
Accepted:	30 June 2023
Published online:	14 March 2024

Autonomous assembly and disassembly by cognition using hybrid assembly cells

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Abstract: Current political, economic, and ecological developments put severe pressure on European industries. Significant value chains depend uniliterally on single suppliers for many industrial resources including, raw materials, semi-finished goods as well as whole components. At the very same time, the European industry needs to get carbon neutral within an unprecedented short time frame. To address these challenges, flexibility, adaptivity[...], and resilience based on adaptive assembly and disassembly systems acting autonomously are key. Existing systems lack crucial capabilities as they focus on output volumes and economic criteria excluding part variance. Furthermore, these systems are unsuitable for small and medium batches due to the necessary investment. The paper presents a novel concept for hybrid-autonomous assembly and disassembly systems based on robot cells added to manual stations. A batch-individual allocation of sub-tasks to the autonomous robot-based system and the manual assembly on-site will lead to maximum flexibility while utilising the advantages of both.

Keywords: autonomous assembly; autonomous disassembly; cognition; intelligent robotics; machine learning; mathematical optimisation; human-in-the-loop.

Reference to this paper should be made as follows: Frieß, U., Oberfichtner, L., Hellmich, A., Fritzsche, R. and Ihlenfeldt, S. (2023) 'Autonomous assembly and disassembly by cognition using hybrid assembly cells', *Int. J. Mechatronics and Manufacturing Systems*, Vol. 16, No. 4, pp.381–398.

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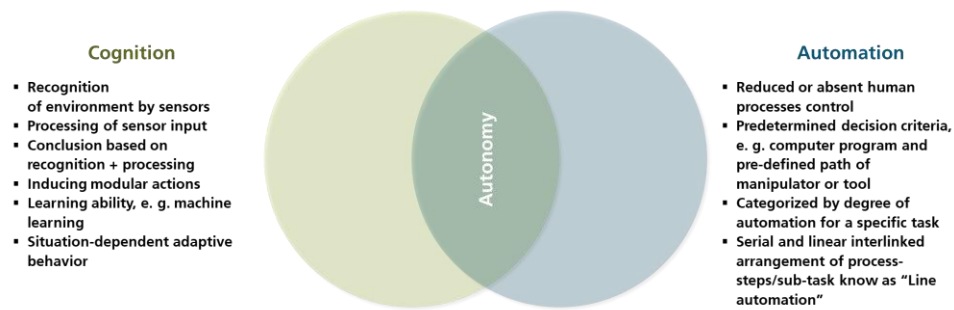
1 Introduction

External shocks like pandemics or global warming as well as societal transformation and labour shortages put extensive pressure on manufacturers and production in general. Historically, the production and assembly of high-value components in developed economies has been increasingly automated to meet market demands and economic pressure. Furthermore, “just in time” supply of semi-finished goods and raw materials based on global supply chains enabled productivity levels unparalleled in history. However, these concepts are not only vulnerable for external shocks and demand fluctuation, but more and more unsustainable for ecological reasons and because semi-finished components and raw materials are no longer available in a constant quality. Classical automation concepts like assembly lines are not suitable to handle fluctuations in quality as well as quantity in general. When dealing with disassembly tasks of used components, the fluctuations of the component state as well as available batch sizes for disassembly grow even exponentially.

Recent developments in robotics and cyber-physical production systems are suitable to handle these challenges. By combining “cognition capabilities” with automation based on robot systems, autonomous (assembly and disassembly) systems become a possibility (see Figure 1).

Figure 1 Autonomy as intersection between cognition and automation based on Damm and Kalmar (2017) (see online version for colours)



These systems can act partially independently from the component’s state and are capable of adapting assembly processes in sequence and process parameters. Their key characteristics are to adapt the assembly and disassembly based on cognition. When individual autonomous systems are linked to each other inside a cyber-physical environment, “matrix” concepts become possible (Foith-Förster, 2022). A desired product can be assembled or disassembled through a range of dynamical linked matrix cells, where each cell is individually controlled and dynamically optimised for specific goal criteria (e.g., energy minimisation) while an overall planning system provides material flow between the cells and compensates external or internal quality fluctuations of input parts.

The successful implementation of robot-based cells for autonomous assembly and disassembly in smart manufacturing possess individual challenges. These are:

i Economic pressure including limited overall equipment cost.

ii Technological requirements, especially in comparison to manual assembly, comprising:

   a short assembly cycle times

   b low failure rates

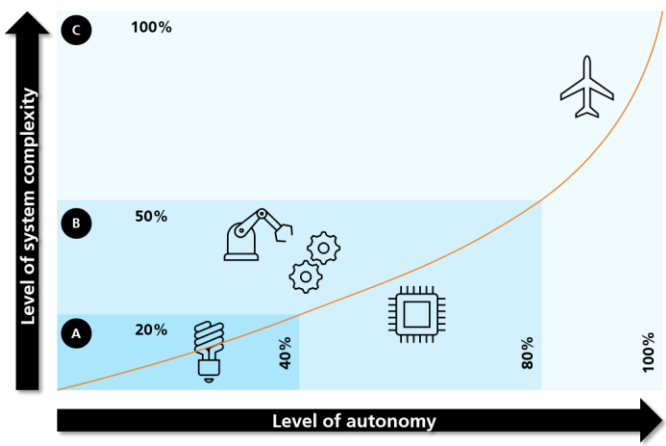
   c flexible scope of the task.

iii Safety requirements and concepts.

These technological requirements still prevent the introduction of fully autonomous robot systems in lots of typical assembly tasks. A key reason is the exponential growth of the system-complexity and necessary capabilities for 100% autonomy (see Figure 2). The individual efforts differ depending on the concrete application: Many tasks include comparatively simple sub-tasks in respect to touch sensitivity like plugging or screwing but also compride difficult sub-tasks like assembly of sealings or springs.

A possible solution hereby combines automation for suitable subtasks by using autonomous robot-based solutions with manual finishing and/or intermediate steps for the subtask, which are not to be automated efficiently.

Figure 2 Required system complexity compared to autonomy-levels (exemplary) (see online version for colours)



Therefore, there are both technological and economic challenges for the successful introduction of such systems. The assembly and disassembly of small and medium batch sizes with almost unlimited configuration options such as "surface-mounted devices" (SMD components such as circuit boards) or control cabinets require a step-by-step approach from 100% manual "craftsmanship" to 100% autonomous automation. The paper presents such a concept by qualitatively describing a hybrid-autonomous assembly station and identifying important technological requirements (Section 3). Research question include – but are not limited to:

- What hardware and software modules are necessary for an autonomous assembly of small batches? (Section 3.1).
- How is it possible to dynamically distribute subtasks depending on the currently available resources for such a hybrid cell? (Section 3.2).
- How is it possible to execute a process autonomously from the start and optimise it afterwards step by step? (Section 3.3 and particular Section 4.2).

2 State-of-the-art

Autonomous assembly – and disassembly – systems including their necessary skills in an industrial environment are a comparatively new research topic. Success stories of industrial applications are even rarer and vary in respect to their autonomy level. The first considerations in the academic environment based on early robotics appeared more than 30 years ago (Hörmann and Rembold, 1991), but there was no further development of the research field or use in the industrial environment. Scholz-Reiter and Freitag (2007) summarise the state of the art around 2005. Typically, autonomous systems were considered in respect to space applications. In these applications, holistic autonomy is necessary per definition. The task assignment including task sequences and task to robot allocation is discussed in Moser et al. (2022) for space-assembly applications. Roa et al. (2022) provides a potential analysis of robotic technology for autonomous assembly of large space telescopes including demonstrators of the EU project prototype of an ultra large structure assembly robot (PULSAR). Schnellhardt et al. (2022) proposes the utilisation of an autonomous segmentation- and assembly- based process chain to manufacture large components on small machines in a scalable manner. Olszewska et al. (2017) describes an ontology standard for the description of autonomous robots. Weyrich and Wang (2013) developed one of the very first architectures for automated disassembly of batteries. Gronau et al. (2016) developed a methodology to define an optimal autonomy level of cyber-physical productions systems by simulation. He already provides key approaches for central challenges in disassembly like multi-agent system for the component identification based on database detection using image processing as well as agent-based sequencing. In many respects challenges, in autonomous vehicles and autonomous robots for service tasks are the very same as in industrial robots for assembly. Typical key technology enablers includes machine learning and/or artificial intelligence approaches. Prominent examples are robots for transportation purposes like Atlas® or Spot® from Boston Dynamics (Guizzo, 2019).

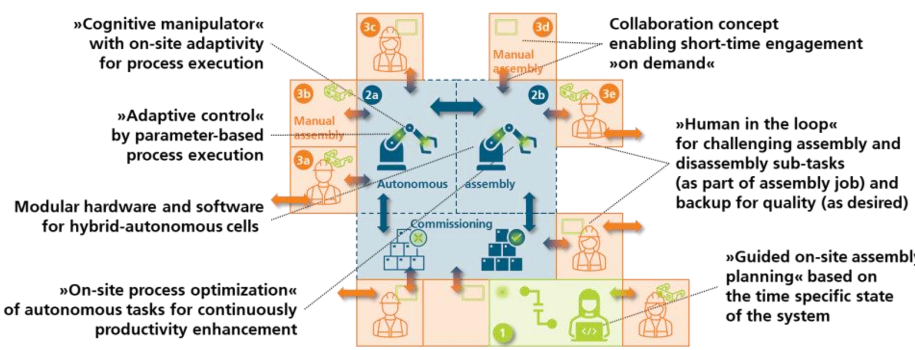
A new approach to organise production and assembly systems to increase resilience as well as flexibility is through the flexible linking of individual production cells and is often referred to as “matrix production” (Ihlenfeldt et al., 2021). To achieve resilience and flexibility, several (semi-) autonomous production cells are combined with each other in a task-driven but not material-flow manner. However, they are orchestrated by a subordinate layer which individually plans with the capabilities of the cells and also organises material transport with autonomous guided vehicles: The linkage always remains temporary and is in sharp contrast to classical automation systems with strict link between process steps, which are typically referred as “line automation”. Furthermore, a more futuristic concept of flexible and demand responsive factory setups is shown in

Hellmich et al. (2020). In both cases the complex interaction and scheduling of required tasks and sub-tasks between the systems to realise whole process chains is beside the scope of the paper. Examples include the usage of Artificial Intelligence to solve the scheduling as described in Rinciog and Meyer (2021, 2022) as well as approaches for intralogistics based on matrix concepts such as Li et al. (2022). The core problem to dynamically shift tasks between individual cells and distribute not only the parts but also dynamic data models to parametrise skill-based controls is subject to extensive research. However, no matter of individual approaches on the planning level all these concepts require a selection of adaptive, autonomous production and/or (dis-)assembly cells to provide their capabilities to the planning layer and execute this kind of production.

3 Key enablers for autonomous system task realisation

A concept for an autonomous hybrid assembly cell is thereafter derived based on the general sequence of autonomous system "cycles" into: recognition – (sensor data) processing – acting. This system is principally capable to exercise a broad range of tasks depending on current requirements and the parametrised task-description. Figure 3 depicts key technologies for such a system, which represent Level 4 capabilities of autonomous systems following concepts of autonomy in autonomous driving (Gamer et al., 2019). An exemplary example of task distribution and sequential process planning between autonomous and manual assembly activities is described in detail in Section 4.1 and Figure 5.

Figure 3 Concept of hybrid-autonomous assembly cell with key enabler technologies, numbers represent process steps detailed in Section 4.1 and in Figure 5 (see online version for colours)



The matrix production concepts outlined in the prior art typically provide a central or cloud-based planning level in which all tasks in a process chain are decomposed into subtasks, including transfer operations and the assignment to specific assembly cells. This also includes resource planning, both on the plant side in terms of necessary skills, necessary tools and available capacities, as well as the requirement for components.

The concept presented here aims to describe the overall performance of the autonomous assembly system, including its manual assembly stations, at a higher level of abstraction and thus makes global planning easier and more efficient. Based on so-called hierarchical models of machine learning, such planning can be understood as hierarchical planning. It leads to more flexibility and significantly less demanding planning requirements at factory or cloud level.

However, this increases the demands on the local planning of task distribution within a cell, especially between autonomous assembly steps and manual steps. In addition, this type of organisation of matrix-based production requires distributed access to available resources and direct communication between the autonomous hybrid cells and the intralogistics.

Then, key factors for these hybrid autonomous assembly and disassembly cells will be discussed in detail. First, adaptive process execution based on hardware – in terms of technical-mechanical skills – and software – in the sense of sensory-control-technical abilities – requirements are described in Section 3.1. The actual assisted planning of the task distribution and its mathematical formulation for the central step of the assignment to autonomous and manual assembly steps takes place in Section 3.2 or, based on an example, in Section 4.1. An optimisation of the autonomous assembly steps based on this with the aim of higher productivity with decreasing use of resources is outlined in Section 3.3 and then deepened and mathematically supported by the application example in Section 4.2.

Specific skills are required to realise the hybrid part of the proposed system. In particular, the dynamic interaction between the autonomous robots and the human workers is not trivial. The approach does not propose a full collaboration concept where robot and human interact at the same time. Although this is a basic option, which is also extensively the subject of current research and development. Typically, however, it reduces the possible dynamics of both robots and human actors and also requires specific resources such as specific robot types and available controllers. Therefore, in the present approach, a serial execution of the sub-processes with a defined transfer point and adapted security concepts such as physical and virtual barriers is propagated. A detailed description of the corresponding concept goes beyond the content of the publication.

3.1 Adaptive process execution requirements for manipulator and adaptive control

To implement the described hybrid-autonomous cell concept, technical-mechanical and sensory-control-technical skills are required, which are necessary for an adaptive process execution. These include – but are not limited to – the following:

Skill 1: "Cognitive manipulator unit" with on-site adaptivity for process execution

a Local sensing unit comprising sensors and image analysis (Abicht et al., 2021).

b Local data processing capability either in the machine controller or an edge device for adaptive process execution.

c Process parallel recording of assembly progress, for example optical tracking, with target/actual comparison as the basis for subsequent parameter-based process control.

d Local fine positioning or path adjustment with the help of a parameterisation of certain values that takes place in process without fundamentally replanning.

e Local process monitoring as digital process twin for on-site quality control.

Skill 2: "Adaptive control" by parameter-based process execution

a Library of skills by means of pre-defined control blocks with basic functionality, standardised interfaces and possibility to change parameters on the fly.

b Subordinate programming architecture to compose skills to jobs.

c Interfaces to change job parameters for workers (human machine interface (HMI) in the commissioning phase) or adaptive process execution engine (through adaptive automatic mode via e.g., OPC UA).

d Adaptive decision making for parameter-adaption and situational switching between assembly skills.

e Controller integration of optical and force sensors.

An example of the local process execution using a cognitive manipulator unit is a multi-stage, adaptive unscrewing depending on the state of the individual screw connection:

i normal unscrewing with nominal torque

ii gradual increase in torque

iii superimposition through smoldering torque application

iv process disruption and human intervention.

An alternative example is the process of plugging various electrical components onto a printed circuit board, with the capacitors being placed on a robot-based adaptive-autonomous basis. This example is deepened in Section 4.

3.2 "Guided onsite assembly planning" for distributed control intelligence

Implementing such a system requires an adaptive control concept for the (local) overall process with embedded sub-programs for dynamic adjustment of parameters during process execution and event-based triggering for subsequent sub-steps or handing over to operators for manual execution of certain sub-steps.

The onsite (dis-)assembly planning includes the following capabilities:

Capability 1: The overall assembly task is decomposed into sub tasks based on equipment availability as a digital data model. The data model, e.g., an OPC UA based model, is transferred and available on-site and includes the digital representation of all necessary resources like grippers, robots and human workers for an individual cell.

Capability 2: The – pre-planned and retrievable from the data model – process steps for the individual sub-tasks and their chronological sequence are checked and, if necessary, rearranged or adjusted in terms of time.

Capability 3: Each individual process section of a subtask is scheduled and parameterised depending on the individual cell status, for example, depending on the individual path from the provision of a component to its position on the assembly group.

Capability 4: Based on assisted planning, resources are actively requested dynamically (e.g., in the sense of being provided by autonomous industrial trucks). The resources include, among other things, components that are required to assemble the assembly. Required resources also include necessary manual assembly capacities.

A central task is the optimal distribution of the sub-processes into autonomous and manual assembly steps. Due to the changing availability, both in terms of capacities of the autonomous robot-based cell components and the availability of manual assembly capacities, it is a challenge. With the (assisted) parallel planning of several batches of components, an objective, mathematically reduced distribution is essential for optimal cell occupancy. Such a mathematical prioritisation, which is part of the assisted planning, is described below.

First the notation is introduced in Table 1.

Table 1 Notation for formulation given in equation (1)

v	Number of different options to choose between to fulfil the tasks. E.g., autonomous, manual (Could be multiple manual workers with different wages or assembly cells with multiple costs, …)
m	Number of individual sub-tasks that need to be considered to achieve the overall task
n	Number of resource fields that will be considered, e.g., costs, energy/carbon, time
$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,v} \\ \vdots & \ddots & \vdots \\ x_{m,v} & \cdots & x_{m,v} \end{bmatrix}$	Matrix that indicates which task is done by whom. With $x_{p,j}$ for $\forall p \in \{1,\dots,v\}$ and $j \in \{1,\dots m\}$ indicating if the task j is done by option p
$k = \begin{bmatrix} k_1 \\ \vdots \\ k_n \end{bmatrix}$	Given the proportional importance weighting of resource fields to be considered With k_i for $i \in \{1,\dots,n\}$ being the proportion of resource field i
$R^p = \begin{bmatrix} R^p_{1,1} & \cdots & R^p_{1,m} \\ \vdots & \ddots & \vdots \\ R^p_{n,1} & \cdots & R^p_{n,m} \end{bmatrix}$	Resources necessary for the assembly process of type p in the resource fields. With $R^p_{i,j}$ for $i \in \{1,\dots,n\}$ and $j \in \{1,\dots,m\}$ being the value needed for resource field i for fulfilling task j
$c = \begin{bmatrix} c_1 \\ \vdots \\ c_p \end{bmatrix}$	Help variant to determine how much transmission needs to be taken into account
γ	Cost of transitioning between different task-fulfilling options

With this knowledge about the variables, the optimisation problem can be explained more easily. It is first formulated and then each line and its derivation are explained.

The formula can be described mathematically as follows:

$$\min_X \sum_{i=1}^{n} k_i \left[\sum_{p=1}^{v} \left[\sum_{l=1}^{m} \frac{\left(R_{i,l}^{p} \cdot x_{p,l}\right)}{\max\limits_{j=1,\dots,m} R_{i,j}^{p}} \right] \right] + \gamma \cdot \left[\left[\sum_{p=1}^{v} c_p \right] - 1 \right] \tag{1}$$

whereby

$$\sum_{i=1}^{n} k_i = 1 \tag{2}$$

$$0 \le k_i \le 1 \qquad \forall\, i \in \{1,\dots,n\} \tag{3}$$

$$\sum_{p=1}^{v} x_{p,j} = 1 \quad \forall j \in \{1,\dots,m\} \tag{4}$$

$$\sum_{j=1}^{m} x_{p,j} \le m \cdot c_p \qquad \forall\, p \in \{1,\dots,v\} \tag{5}$$

$$x_{p,j} \in \{0,1\} \quad \forall p \in \{1,\dots,v\} \text{ and } j \in \{1,\dots,m\} \tag{6}$$

$$c_p \in \{0,1\} \quad \forall\, p \in \{1,\dots,v\} \tag{7}$$

The objective function equation (1) adds up the weighted costs of autonomous, manual and transfer efforts for every necessary sub-task m for every resource field n of a given (assembly) process p. More precisely, the objective function equation (1) is a minimisation over the variable X, i.e., the function searches for a minimal solution over the possibilities of task distribution. The objective to be minimised is the sum of two parts. First, the left part is considered; at the lowest level is a fraction. The denominator is a maximisation problem of the necessary resources. The resource field is fixed, and the value of the maximum overall sub-tasks is searched. The reason behind this is to standardise the added values. For every resource field, the factor combined with $R_{i,l}^{p}$ from the numerator will be between 0 and 1 without unity, making it easier to consider different resource fields at once. The sums over p and l add up over all sub-tasks, and for the different options, the factor k_i comes into play to account for how the other resource fields are weighted. If only this part was minimised, the sum would consider how high the relative production costs would be. The last part considers the number of necessary switches between different task performers. These must be accounted for because switching between a manual worker and a robot takes additional time, for example. The γ is just the cost factor that needs to be considered. So a few things must be true for the formula to make sense. First, each sub-task must be accounted for, which is insured with constraint in equation (4), by checking that the summed values in X equal one for each sub-tasks. Together with equation (6), this ensures that each sub-task will be executed by one working station either autonomously or manually and not be split up since $x_{p,j}$ can only be 0 or 1. Constraint in equation (5) ensures that the additional switching costs between different options are accounted for correctly. Since equation (7) secures that c_p can only be 0 or 1, as soon as one of the X values associated with the option p is 1, c_p must be 1 as well. The m on the right side ensures the equation is satisfactory even if the entire thing is produced in one workstation. The last thing to explain is k_i. It is chosen to add up to 1. This is equal to the proportional importance of all resource fields adds up to 1. Equation (3) states that none of the weights can be negative, as this would render the optimisation useless since everything would be directed towards maximising that resource field, regardless of how useful it is.

De-facto the exact determination of the weightings (k_i) is complex, depending on the current situation at an individual production site and beyond the scope of the paper. Considering the availability of several hybrid autonomous assembly systems, e.g., a matrix concept, the solution becomes even more complex. Particularly challenging is the definition of the weighting factors k_i between the different resource domains m. A possible solution is calculating the optimal solution for every domain separately and having a decision-making process by trained human planners on-site depending on the urged demand, e.g., minimal assembly time for critical components or minimal costs and energy resources for components which will be delivered or used later.

3.3 "On-site process optimisation" for continuously productivity enhancement

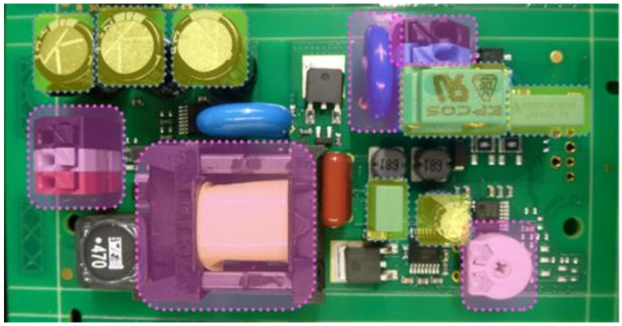
Even an optimal design and commissioning of such an autonomous robot-based assembly system will initially not match the performance of skilled blue-collar workers. One possibility to address these challenges is to optimise the system in a digital environment, commonly known as "Virtual Commissioning" (Ihlenfeldt et al., 2021). While this approach is promising in many applications, it requires large amounts of upfront resources and time. Depending on the application an "on-site process optimisation" of an initially non-optimal assembly and disassembly can be promising as well and is described in detail afterwards:

- i Adaptive data-processing and control interaction for robot-path definition using actual object-robot position.
- ii In-process criteria for process interruption based on sensor-based process supervision, e.g., position of (dis-)assembly parts.
- iii In-process optimisation of sub-tasks; see the next section (see Section 4).

4 Application example: hybrid-autonomous assembly of circuit boards

A broad range of assembly tasks are not automatable due to low batch volumes, uncontrollable variance in the task states as well as high limits for the reproduction of human skills like the sensing of the human hand. These challenges are even more severe in disassembly tasks per definition as already discussed. The assembly of electrical circuit boards represents one such application (Figure 4). Typically, one part of the task consists in mounting capacitors of different sizes but equal geometry to the board while follow-up tasks include the application-individual assembly of a broad range of electrical components (yellow for autonomous assembly and purple for manual assembly in Figure 4).

Figure 4 Electrical circuit board for control of luxury lightning systems; yellow – autonomous assembled capacitors / purple – manually assembled components (see online version for colours)

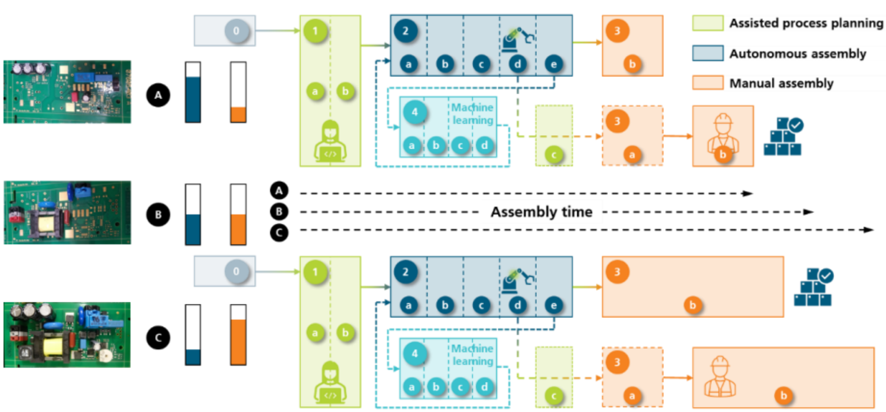


Developing and commissioning a robot-based autonomous system for all sub-tasks would result in an extremely complex and failure-prone system. The system would require complex and expensive cognition capabilities like fast 3D computer vision, multiple complex grippers as well as high level (Edge-) information technology (IT)-infrastructure to process large amounts of process data live. However, automatisation of only the first part – the mounting of the capacitors – would already relieve the human labour workload significantly. The necessary modular robot-based assembly system for this step could be realised for a fracture of the costs of a full autonomous system.

4.1 Overall process planning and execution in detail

Figure 4 depicts the approach and visualises the different autonomous and manual tasks depending on exemplary batches of electrical circuits for control elements of high-level lightning systems depending on their complexity level (distinguished as A-B-C in Figure 5).

Figure 5 "Batch-individual" process for hybrid assembly of electrical circuits (see online version for colours)



The overall process can be clustered in the following sub-tasks (steps 1–4 depicted in Figure 5):

Step 0: "Process planning": The assembly of a specific batch is planned software-supported including all necessary process steps and assigned to a certain modular assembly system. Skill-descriptions for the hybrid assembly-stations need to include:

a Skill-capabilities of the equipment, e.g., robot size and range, available sensors and cognition capabilities.

b Manual-labour integration capabilities, e.g., the available manual workplaces at the specific system as well as the collaboration and commissioning concept.

c Current state of the system as well as the available workforce, e.g., already allocated batches and available human labour.

d In-site availability of resources (energy, raw material, semi-finished goods, e.g., microcontrollers) at a given time.

Step 1: "Guided on-site assembly planning": The task-allocation between the autonomous assembly (in blue in Figures 3 and 5) and the manual assembly (in orange in Figures 3 and 5) is done locally "on site" (in green in Figures 3 and 5). This process step is not necessary for every autonomous system but enables short term adaption through skilled personnel:

a The process planning is double-checked, and the task-allocation is detailed considering the actual situation on-site.

b If necessary, assembly personnel can be trained on-site (lower right in Figure 3) or on the job (orange boxes 3a–3d in Figure 4) using guided assembly, e.g., by augmented reality (AR)-systems.

c If autonomous assembly steps fail (step 2-d in Figure 5) the subtasks are re-scheduled between the autonomous robots and the manual assembly stations.

Step 2: "Autonomous process execution": The autonomous process-steps are executed and constantly monitored (in blue in Figure 5). The assembly process is digitally tracked as Predictive-Quality approach to support life information's of the assembly-state of the current batch:

a Monitoring of part-orientation and flexible robot path adaption based on suitable sensors, e.g., distance sensors based on triangulation or depth-sensing camera.

b Sensor-acquired parameters like position information of key-areas are compared to the nominal parameters based on e.g., CAD models.

c The path is dynamically adjusted based on the calculated delta, e.g., by shifting the coordinate system or adjusting skill parameters for maximum performance with minimal hardware resources.

d Adaptive assembly process control based on additional sensors: torque sensors are used for matching the assembly tool to the component's requirements.

e Assembly / Disassembly operation by tool, e.g., plugging of the capacitors.

Step 3: Manually finishing the assembly task (in orange in Figure 5):

a Additional unplanned manual assembly steps, when necessary.

b Planned manual assembly steps depending on the individual batch.

Step 4: "Machine-learning based in-process optimisation" of the autonomous tasks:

a The plugging of the capacitors into the electrical circuit board is initially executed carefully using minimal dynamic and double-checks like confirmation of the puncture position using laser sensors.

b For every successful task the parameters are monitored and stored on-site (at an Edge infrastructure).

c A mathematical optimisation algorithm minimises the potential assembly errors ("hitting the puncture hole") for the assembly step using in-process data.

d The process is constantly adjusted to increase the performance of the assembly step, e.g., the cycle time for the capacitor plugging is reduced by increased robot dynamics.

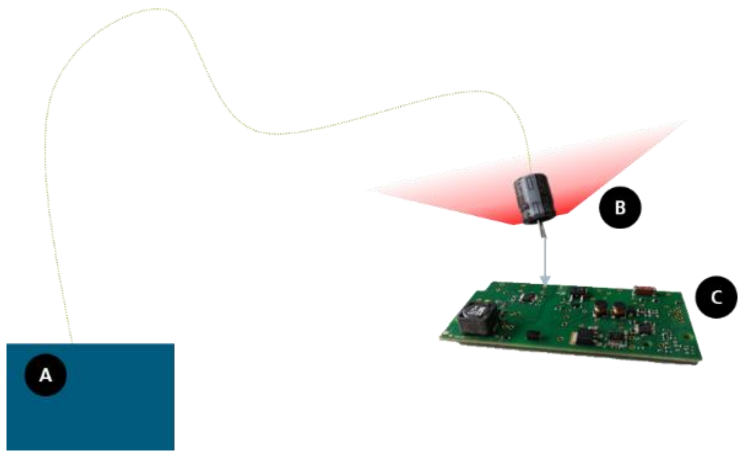
4.2 Machine learning in-process optimisation of plugging capacitors

Process optimisation based on machine learning is a key factor for expanding the scope of autonomous assembly processes. For almost any assembly task, the required assembly time is typically higher when performed by a flexible robot system than when performed manually. A classic example is pick-up operations by robots of loose bulk goods. In certain application areas it is possible and state of the art to implement such processes with autonomous robots using 3D camera systems, flexible grippers and live path planning. For small electrical components, this process usually takes much longer compared to manual execution. However, unskilled workers also take longer in comparison and an autonomous system based on flexible robots can assemble around the clock. In any case, the robot must reproduce human learning at least to some extent when executing a certain sub-process. Therefore, a mathematical optimisation approach for placing the capacitors on the circuit boards is presented below. The initial state of the process is a capacitor that has been gripped in a defined manner and whose position is known to the robot controller (state A in Figure 6).

Based on a predefined trajectory of the robot, the capacitor is moved to position B in Figure 6. This position is above the circuit board, whereby the specific value depends on the individual circuit board. During the movement to position B, a sensor – for example a camera system that can record a moving object – monitors the position of the capacitor. An algorithm checks if the capacitor moves inside a virtual tunnel to reach the right position for plugging on the board at position C in Figure 6.

If the capacitor position is within the tolerance, the robot will decelerate as planned until position C without corrections ($x \leq \delta$). If the position is slightly above tolerance ($\delta < x < 2\delta$), the position is corrected while continuing to travel from position B to C parallel to the deceleration process. If the position of the capacitor is significantly out of tolerance ($x \geq 2\delta$), the robot will stop as quickly as possible without plugging and move the capacitor to position B again and/or throw the capacitor in a "process error box". Afterwards, the position of the capacitor is adjusted at position B and slowly moved to position C and plugged or a new capacitor is gripped, and the process restarted at position A.

Figure 6 In-process optimisation of capacitor-plugging using intelligent camera-based process execution (see online version for colours)



For in-process optimisation of the overall plugging time, the initial speed of the robot along the path between A and B is slow so to plug all capacitors safely. Based on this initial condition, the robot's speed along the path is increased step by step to optimize plugging times. As the speed increases, the number of out-of-tolerance approaches at position B increases until the overall time over many plugging processes increases again due to a high proportion of "failure plugging's".

Therefore, a function representing the average "plugging effort" can be defined as the following:

$$f(a) = \frac{1}{n}\left[\sum_{i=1}^{n}\left[a_{i,1} + \theta \cdot h\left(a_{i,2}\right)\right]\right] \quad (2)$$

$$h(x) = \begin{cases} x \le \delta & 0 \\ \delta < x < 2\delta & 1 \\ x \ge 2\delta & M \end{cases} \quad (3)$$

whereby

n	Given number of repetitions (per speed)
$a = \begin{bmatrix} a_{1,1} & a_{1,2} \\ \vdots & \vdots \\ a_{i,1} & a_{i,2} \end{bmatrix}$	Matrix with the measured input information. With $a_{i,j}$ with $i \in \{1,\ldots,n\}$ indicating the repetition and $j = 1$ identifying it as the measured time from A to B and $j = 2$ the deviation of the goal B
θ	Punishing weight for not being within the allowed deviation of point B
$h()$	Function to rate the deviation
δ	Allowed deviation from point B
M	Large number

The function f itself averages the sum over all repetitions. Each repetition is the sum of the time it takes to get from A to B $\left(a_{i,1}\right)$ and the additional time for adjustment before it can reach C. The last part depends on help function h; the function has three cases that align with the described cases before. No adjustment is equal to 0 since there is no extra cost/time; for minor adjustments, the value is 1, so in the total function, the penalising weight is taken once, and for the last case, which is out of the range for minor adjustments, the time penalty should be high, so a large number M is returned.

By applying the approach to multiple capacitors on several different products of circuit boards the robots "learn" their individual optimum for a certain combination.

Compared to possible alternatives for in-process optimisation as AI models the discussed approach can be implemented easily in parallel to the running process. No large amounts of upfront training data are necessary and no performance hardware. The approach applies to plugging operations of many electrical components on circuit boards with minor adaptions. Further research will examine physical test setups, the algorithm's optimisation, and the strategy to find optimal path speeds.

5 Conclusion and future work

The successful implementation of autonomous assembly and disassembly systems in production is associated with certain specific challenges that are found in autonomous systems of other application areas, e.g., autonomous driving or autonomous service robots, are not available. Based on the description of the challenges, the contribution develops a concept for a robot-based hybrid (dis)assembly system for the dynamic planning of subtasks between autonomous and manual system elements. Key factors and their properties are described. Possible optimisation approaches are described for the most important planning challenges. The assembly of printed circuit boards serves as a concrete application example. For this example, a mathematical optimisation for efficiently plugging capacitors on electrical circuit boards is described. Inadequate productivity when loading with 6-axis robots has proven to be the main obstacle. On this basis, a multi-criteria target function was introduced that takes into account different resources such as time, available carbon budget or energy consumption. The optimisation of this target function should then be implemented in practice and critically evaluated as a subsequent step.

Currently, the detailed development of the described optimisation approach for the application of capacitor assembly is planned as the next step. A high-performance camera system is to be used for in-process recording of the web movement. A pattern recognition continuously checks the necessary path fidelity of the current capacitor for a successful placement on the circuit board. A parameter set is to be dynamically adjusted through continuous communication with the robot controller to correct any deviations. The necessary training for generating the pattern is to be implemented with the help of synthetically generated paths from a virtual environment.

Acknowledgement

The paper was co-funded inside the MODUL4R project as part of the Horizon Europe funding program for research and innovation by the European Union.

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